Journal of Risk and Financial Management

Volume 1

2008

Published By

University of Ontario Institute of Technology

Editor

Dr. Raymond A. K. Cox

Journal of Risk and Financial Management

DO REITS OUTPERFORM STOCKS AND FIXED-INCOME ASSETS? NEW EVIDENCE FROM MEAN-VARIANCE AND STOCHASTIC DOMINANCE APPROACHES

Thomas C. Chiang [a]
Hooi Hooi Lean [b]
Wing-Keung Wong [c]

ACKNOWLEDGMENTS

This research is partially supported by Drexel University, Universiti Sains Malaysia, and Hong Kong Baptist University. The second author would also like to acknowledge the Universiti Sains Malaysia RU Grant No. 1001/psosial/816094.

---

[a] Department of Finance, LeBow College of Business, Drexel University, 32nd and Chestnut Streets, Philadelphia, PA 19104 USA. Email: chiangtc@drexel.edu
[b] School of Social Sciences, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia Email: hooilean@usm.my
[c] Department of Economics, Hong Kong Baptist University, Kowloon Tong, Hong Kong. Tel: (852)-3411-7542, Fax: (852)-3411-5580, Email: awong@hkbu.edu.hk
[*] Corresponding author: Thomas C. Chiang, Tel: 609 668-1155, Fax: 609 265-0141

DO REITS OUTPERFORM STOCKS AND FIXED-INCOME ASSETS? NEW EVIDENCE FROM MEAN-VARIANCE AND STOCHASTIC DOMINANCE APPROACHES

ABSTRACT

This paper re-examines the performance of REITs, stocks, and fixed-income assets based on the preferences of risk-averse and risk-seeking investors using mean-variance and stochastic dominance approaches. Our findings indicate no first-order stochastic dominance and no arbitrage opportunity among these assets. However, our stochastic dominance results reveal that in order to maximize their expected utility, the risk-averse prefer fixed-income assets over real estate, which, in turn, is preferable to stocks. On the other hand, to maximize their expected utility, all risk-seeking investors would prefer to invest in stocks than in real estate, but real estate, in turn, is preferable to fixed-income assets.

Keywords: stochastic dominance, risk, REITs, stock, fixed-income assets, risk-aversion, risk-seeking.

1. INTRODUCTION

The collapse of the dot-com mania in 2000 led investors to reshape their market expectations. Instead of sticking to the traditional choice between stocks and bonds, investors, motivated by expectations of falling interest rates, switched to real estate markets to maximize their portfolio returns. Investments in real estate are known to trade less frequently and bear high transaction costs. Alternatively, real estate investment trusts (REITs) offer investors a better instrument, one that is more liquid and has lower transaction costs compared with traditional real estate investment.

In recent years, REITs have developed into a relatively more efficient real estate instrument. Starting in 1992, REITs have grown significantly in both size and number. This is due to the fact that REITs pay stable dividends and are less sensitive to the state of the general economy. Lee and Stevenson (2005) document that REITs provide diversification benefits to mixed-asset portfolios, benefits that appear to come from both the enhanced returns on REITs and their reduced risk.

The statistical analysis of the relationship between real estate returns and the returns on other asset classes is important to investors, since it provides information to guide portfolio management. In the standard portfolio approach, the return differentials should reflect the risk differentials or other financial characteristics. Since returns on financial assets are often found to display skewness and leptokurtosis (see, e.g., Peiró, 1999; Patton, 2004; Brooks, et al., 2005), investors' concerns about portfolio return distributions cannot be fully captured by the first two moments. Otherwise, the portfolio's true riskiness will be underestimated. This motivates us to conduct a statistical analysis to evaluate REITs against stocks and fixed-income assets by considering the effect of the higher moments of the returns. This paper introduces an alternative technique for examining the performance of these assets that accounts for the preferences of risk-averters and risk-seekers among these assets. In particular, we re-examine market efficiency and the behavior of risk-averters and risk-seekers via a stochastic dominance (SD) approach by using the whole distribution of returns from these assets. To our knowledge, this is the first paper that uses SD techniques to analyze real estate returns.

As stated earlier, empirical studies have shown that asset returns may not be adequately described by the first two moments (Peiró, 1999; Harvey and Siddique, 2000; Patton, 2004; Brooks, et al., 2005; Smith, 2007). In particular, in most situations, the Gaussian assumption does not hold, distribution is skewed to either left or right, and fat tails present in the asset return series. Researchers recognize that using traditional mean-variance (MV) or CAPM-based models to analyze investment decisions is appropriate only when the return series is normally distributed or investors' preferences are quadratic. Since the MV and CAPM criteria are restricted to the first two moments of the data, important information contained in the higher moments is ignored and, hence, group reactions may be neglected and investors may tend to get overconfident and take unsuspected risk. To overcome the shortcomings associated with the MV and CAPM-based models and to investigate the entire distributions of the returns directly, we employ a non-parametric SD approach to analyze the returns of REITs against three stock index returns and two fixed-income investments.

The assumptions underlying SD are less restrictive than those of the MV and CAPM models. In addition, SD that reveals the entire distribution covers all information from the distribution, rather than just the first two moments, as postulated by MV, and requires no precise assessment of the specific form of investors' risk preference or utility function. Comparing portfolios using the SD approach is equivalent to making asset choice by employing utility maximization. It also allows us to determine if an arbitrage opportunity exists among the investment alternatives, so that once an arbitrage opportunity is identified, investors can increase their expected utility, and hence their wealth, by setting up zero dollar portfolios to exploit this opportunity.

Examining the data over the entire sample period of 1999-2005, this study finds that all REITs (except mortgage REITs) dominate the three stock indices but not fixed income investments using the mean-variance criterion. The results also show that there is no first-order SD between REITs and alternative assets, implying that investors cannot increase their wealth by switching from one asset to another. However, REITs stochastically dominate the stock index investments, but they are stochastically dominated by Treasury constant maturity at the second and third order for risk-averters. On the other hand, the reverse holds true for risk-seekers. These results reveal that to maximize their expected utility, all risk-averse investors would prefer to invest in real estate than in the stock market. However, if we compare REITs with fixed-income assets, they would prefer fixed-income assets. On the other hand, to maximize their expected utility, all risk-seeking investors would prefer to invest in stocks than in real estate, which, in turn, is preferable to fixed-income assets.

The remainder of the paper is organized as follows. Section 2 provides a literature review, which motivates us to conduct the SD analysis. Section 3 describes the data and methodologies. Section 4 presents the empirical results and provides our explanation. Section 5 contains the conclusion.

2. LITERATURE REVIEW

Returns on REITs have been extensively studied in the literature. A large and growing body of research examines REITs' efficiency.[1] Some researchers suggest that real estate returns are more predictable than the returns of other assets. Nelling and Gyourko (1998) find evidence that monthly returns on equity REITs are predictable using past performance. However, the predictability is not substantial enough to cover typical transaction costs, so that there is no evidence of unexploited arbitrage opportunities. Ling and Naranjo (2003) find that equity REIT flows are significantly positively related to the previous quarter's flows and negatively related to flows from two quarters ago.

Using a variant of time-series correlations, many researchers have attempted to analyze the determinants of REIT returns. For instance, Peterson and Hsieh (1997) report that the return behavior of REITs is similar to that of a portfolio of small stocks.

[1] Anderson et al. (2000) review the REIT efficiency literature.

Swanson et al. (2002) find that REIT returns are more sensitive to the maturity rate spread between short- and long-term Treasuries than to the credit rate spread between commercial bonds and Treasuries. They also find that REIT returns are significantly related to the default spread on returns and the term spread on interest rates. Moreover, Chui et al. (2003) report that in the pre-1990 period, REIT returns are affected by market momentum, firm size, turnover, and analyst coverage. In the post-1990 period, REIT returns are predominantly affected by market momentum. In addition, there are conflicting results as to whether REIT returns are negatively related to their market-to-book value.

A number of studies (e.g., McIntosh et al., 1991; Khoo et al., 1993) have observed an apparent decline in the market betas of equity REITs. If the decline is of statistical and economic significance, the implication is that estimates of equity REIT betas that rely on historical returns are biased upward. Chiang et al. (2005) find weak evidence for a decline in equity REIT betas based on a single-factor model. However, when the three-factor model is used, the declining trend in equity REIT betas disappears.

Firstenberg et al. (1988) and Liu et al. (1992) have suggested that real estate returns may not be independent over time. They find strong autocorrelation in real estate returns. Sagalyn (1990) and Goldstein and Nelling (1999) show that REITs' risk and return are dependent on business cycles and the direction of market returns. They find that REITs more closely track the return of the stock market in a down market than in an up market. A low beta in an up market may be due to the decline in the relationship between REITs and the stock market.

Numerous studies have tested the efficient characteristics of REITs vis-a-vis the stock market. The evidence has been mixed. Specifically, Ambrose et al. (1992) and Seck (1996) report that equity REITs and the S&P 500 behave as a random walk and find that the real estate and stock markets are not segmented. Kleiman et al. (2002) provides further evidence of random walk behavior and weak-form efficiency in international real estate markets in Europe, Asia, and North America by applying the unit root, variance ratio, and runs tests. On the other hand, Kuhle and Alvayay (2000) find evidence of inefficiency in the price of 108 equity REIT companies during 1989-1998. Jirasakuldech and Knight (2005) find that from 1972 to 2004, efficiency increased for equity REITs and the Russell 2000 index of small capitalization stocks. Some predictability, but not necessarily inefficiency, persists for mortgage REITs and hybrid REITs.

Several studies test the market efficiency hypothesis for REITs by examining the seasonality and predictability of REITs. Colwell and Park (1990) find evidence of seasonality and the January effect in 28 equity REITs and 22 mortgage REITs between 1964 and 1986. Mclntosh et al. (1991) find size effect in REITs: small firms perform better than large firms. Bharati and Gupta (1992) document the profitable trading rules of REITs after transaction costs are considered. Liu and Mei (1992) suggest that expected excess returns on equity REITs are more predictable than those of small cap stocks and bonds. They decompose excess returns into expected and unexpected excess returns to examine what determines movements in expected excess returns because equity REITs are more predictable than all other assets. On the other hand, Liu et al. (1990) and Li and Wang (1995) provide evidence suggesting that REITs and the general stock market are integrated and that there is no predictability in the REIT markets.

Although there is a substantial amount of research on market efficiency, these studies mainly investigate the correlations of dependency over time and/or correlations with other state variables. Very few attempts go beyond the second moments, but there are some exceptions. For instance, Liu et al. (1992) document that co-skewness offers some explanation for REIT returns. However, Vines et al. (1994) and Cheng (2005) cannot find supporting evidence in favor of co-skewness as an explanation for REIT returns. These mixed findings may arise because different statistical tools were used in these studies, some of which may suffer from mis-specification or distributional problems. In this paper, as mentioned in the introduction, we apply an SD approach to analyze the returns of REITs against three stock index returns and two Treasury constant maturities. This approach allows us to examine the first three moments of the return series by focusing on the choice of assets via utility maximization.

3. DATA AND METHODOLOGY

To provide broader and consistent evidence, we use daily returns[2] of all REITs, equity REITs, mortgage REITs, and US-DS real estate in our empirical examination. The data are taken from the National Association of Real Estate Investment Trusts. The index series is based to December 1971=100. To simplify, we call this asset group REITs. We compare REITs with three common stock indices: Dow Jones Industrials, the NASDAQ, and the S&P 500; and two fixed-income assets: the 10-year Treasury note and 3-month Treasury bill rate. Data for the stock indices are obtained from Yahoo Finance; data for the Treasury constant maturities are from the Federal Reserve Bank of St. Louis. The sample covers the period from January 1999 through December 2005.

Most REIT risk/return studies model risk using the CAPM-based model or MV of asset returns. The standard CAPM identifies two types of risk associated with an investment in REITs. For instance, Shalit and Yitzhaki (2002) link the poor empirical performance of betas to non-normality in return distributions and inadequate specification of investor utility functions. Enders (1995) maintains that if the investor's utility function is quadratic and/or the excess returns from holding the asset are normally distributed, an increase in the variance of returns is equivalent to an increase in "risk." The non-normal aspects of the financial data have been modeled by different distributions and fat tails (Loretan and Phillips, 1994; McDonald and Xu, 1995; Smith, 2007). However, closed-form expressions for the density functions of stable random variables are available only for special cases, such as the normal, the Cauchy, and the Bernoulli cases. However, the fat-tailed distributions have no mathematically closed form, making them grudgingly reliant on parameter estimations. To address the issue, Sivitanides (1998) and Sing and Ong (2000) propose that portfolios generated with a downside risk (DR) framework are more efficient than those generated with a classic

---

[2] We also use weekly data to check the robustness and find similar results. Results are available upon request.

MV and have better risk-return trade-offs. However, as pointed out by Cheng and Wolverton (2001), a non-stable return distribution is a problem in the application of DR and modern portfolio theory models. In light of the above considerations and evidence, it is clear that if normality does not hold, the MV criterion may produce some misleading results. To circumvent this problem, we use the SD approach in this paper.

Porter and Gaumnitz (1972) generate a Markowitz MV efficient set of portfolios from 140 stocks and apply first-, second-, and third-degree SD tests. They report that the most significant difference between the MV and SD portfolios is the tendency for SD to eliminate low return-low variance portfolios. Although they conclude that the choice between SD and MV models is not critical, the MV rule can lead highly risk-averse investors to make choices inconsistent with maximizing their expected utility.

For any two investments with variables for profit and return Y_i and Y_j with means μ_i and μ_j and standard deviations σ_i and σ_j, respectively, Y_j is said to dominate Y_i by the MV criterion if $\mu_j \geq \mu_i$ and $\sigma_j \leq \sigma_i$. The MV and CAPM criteria depend on the existence of normal return distributions and quadratic utility functions and are not appropriate if return distributions are not normal or if investors' utility functions are not quadratic (Feldstein, 1969; Hakansson, 1972).

To illustrate the tenets of the SD approach, let F and G be the cumulative distribution functions (CDFs) and let f and g be the corresponding probability density functions (PDFs) of two assets Y and Z, respectively, with common support of [a, b], where $a < b$. Define:

$$H_0^A = H_0^D = h\,,\quad H_j^A(x) = \int_a^x H_{j-1}^A(t)\,dt \quad \text{and} \quad H_j^D(x) = \int_x^b H_{j-1}^D(t)\,dt \qquad (1)$$

for $h = f$ or g , $H = F, G$; $j = 1,2,3$, where the superscript A refers to ascending and the superscript D refers to descending.

We note that H_j^A can be used to develop the SD theory for risk-averters (see, for example, Quirk and Saposnik, 1962; Fishburn, 1964), whereas H_j^D can be used to develop the SD theory for risk-seekers (see, for example, Meyer, 1977; Stoyan, 1983; Wong and Chan, 2007). As H_j^A is integrated from H_{j-1}^A in ascending order from the leftmost point of downside risk, we call the SD for risk-averters ascending stochastic dominance (ASD) and call the integral H_j^A the j^{th} order ascending cumulative distribution function (ACDF) or simply the j^{th} order ASD integral. On the other hand, as H_j^D is integrated from H_{j-1}^D in descending order from the rightmost point of upside profit, we call the SD for risk-seekers descending stochastic dominance (DSD) and call the integral H_j^D the j^{th} order descending cumulative distribution function (DCDF) or simply the j^{th} order DSD integral for j = 1, 2 and 3[3] and for $H = F$ and G. These definitions can be used to examine both risk-averse and risk-seeking preferences. FASD refers to first-order (ascending) stochastic dominance, SASD refers to second-order (ascending) stochastic dominance, and TASD refers to third-order (ascending) stochastic dominance for risk-averters. Likewise, similar definitions are applied to risk-seekers. Particularly, FDSD refers to first-order (descending) stochastic dominance, SDSD refers to second-order (descending) stochastic dominance, and TDSD refers to third-order (descending) stochastic dominance for risk-seekers.

The most commonly used ASD rules contain three broadly defined utility functions for risk-averters:

- investors exhibit non-satiation (more is preferred to less) under FASD;
- investors exhibit non-satiation and risk aversion under SASD;

[3] In his analysis of 1281 mutual funds, Vinod (2004) recommends employing the fourth-order SD to choose among investment prospects. However, the first three orders are the most commonly used in SD for empirical analyses. We shall keep this convention in this paper.

- investors exhibit non-satiation, risk aversion, and decreasing absolute risk aversion (DARA) under TASD.

Similarly, the most commonly used DSD rules correspond with three broadly defined utility functions for risk-seekers:

- investors exhibit non-satiation (more is preferred to less) under FDSD;
- investors exhibit non-satiation and risk seeking under SDSD;
- investors exhibit non-satiation, risk seeking, and decreasing absolute risk aversion (DARA) under TDSD.

It is important to differentiate the SD rules for risk-averters and risk-seekers, respectively. These rules are given in the following sub-sections.

3.1. SD for the Risk-Averse

Following Quirk and Saposnik (1962), Fishburn (1964), and Hanoch and Levy (1969), we outline the SD rules for risk-averters as:

i. Asset *Y* dominates asset *Z* by FASD (denoted $Y \succ_1 Z$ or $F \succ_1 G$), if and only if $F_1^A(x) \le G_1^A(x)$;

ii. Asset *Y* dominates asset *Z* by SASD (denoted $Y \succ_2 Z$ or $F \succ_2 G$), if and only if $F_2^A(x) \le G_2^A(x)$;

iii. Asset *Y* dominates asset *Z* by TASD (denoted $Y \succ_3 Z$ or $F \succ_3 G$), if and only if $F_3^A(x) \le G_3^A(x)$; (2)

for all possible returns *x*, with strict inequality for at least one value of *x*, where F_j^A and G_j^A are defined in (1) for $j = 1,2,3$.

The existence of SD implies that investors' expected utility is always higher under the dominant asset than under the dominated asset, and, consequently, the dominated asset would never be chosen. Note that a hierarchical relationship exists in SD:

first-order SD implies second-order SD, which, in turn, implies third-order SD. However, the converse cannot be true: a finding that second-order SD exists does not imply the existence of first-order SD. Likewise, a finding that third-order SD exists does not imply the existence of second-order SD or first-order SD. Thus, in practice, the lowest dominance order of SD is reported. Moreover, it is generally recognized that asset *Y* stochastically dominates asset *Z* at first order, if and only if there is an arbitrage opportunity between *Y* and *Z*, such that the investor will increase wealth as well as utility if investment is shifted from *Z* to *Y* (Jarrow, 1986). Hence, the SD approach provides a tool for revealing arbitrage opportunities among investment prospects. Hanoch and Levy (1969) indicate risk-averse investors will increase their utility but not necessarily their wealth by switching portfolios. The existence of second-order or third-order SD does not imply any arbitrage opportunity, and neither does it imply the failure of market efficiency or market rationality.[4]

3.2. SD for Risk-Seekers

The theory of SD for risk-seekers is also well established (Hammond, 1974; Meyer, 1977; Stoyan, 1983; Levy and Wiener, 1998; Wong and Li, 1999; Anderson, 2004). The SD rules for risk-seekers are:

i. Asset *Y* dominates asset *Z* by FDSD (denoted $Y \succ^1 Z$ or $F \succ^1 G$), if and only if $F_1^D(x) \geq G_1^D(x)$;

ii. Asset *Y* dominates asset *Z* by SDSD (denoted $Y \succ^2 Z$ or $F \succ^2 G$), if and only if $F_2^D(x) \geq G_2^D(x)$; and

iii. Asset *Y* dominates asset *Z* by TDSD (denoted $Y \succ^3 Z$ or $F \succ^3 G$), if and only if $F_3^D(x) \geq G_3^D(x)$; (3)

for all possible returns *x*, with strict inequality for at least one value of *x*, where F_j^D

[4] See Jarrow (1986), Falk and Levy (1989), Bernard and Seyhun (1997), and Larsen and Resnick (1999) for more discussion about applying SD to test for market rationality and market efficiency.

and G_j^D are defined in (1) for $j = 1, 2, 3$.

Owing to its superiority in comparing prospects, the SD theory used to compare returns for both risk-averters and risk-seekers is well established. The advantages of SD have motivated previous studies to use SD techniques to analyze many financial puzzles (see, e.g., Seyhun, 1993; Larsen and Resnick, 1999; Kjetsaa and Kieff, 2003). Unfortunately, previous research was unable to determine the statistical significance of SD. However, recent advances in SD techniques allow researchers to determine the statistical significance. To date, the SD tests for the risk-averse have been well developed and documented by McFadden (1989), Klecan et al. (1991), Kaur et al. (1994), Anderson (1996, 2004), Davidson and Duclos (2000), Barrett and Donald (2003), and Linton et al. (2005).

Although Barrett and Donald's (2003) test is a powerful instrument and Linton et al.'s (2005) test is useful because it is an extension of the Kolmogorov-Smirnov test for FASD and SASD by relaxing the iid assumption, the SD test developed by Davidson and Duclos (DD, 2000) is found to be one of the least conservative and most powerful SD tests, as argued by Tse and Zhang (2004) and Lean et al. (2006). We report the results of DD's test to determine whether statistically significant SD occurs between REITs and other assets and skip those of BD's and Linton et al.'s tests, since the results of both BD's and Linton et al.'s tests are consistent with those of DD's test.

3.3. Davidson and Duclos Test

To elucidate the DD test, let $\{(y_i, z_i)\}$ be pairs of observations drawn from the random variables *Y* and *Z* with distribution functions *F* and *G*, respectively. For a grid of pre-selected points x_1, $x_2 \ldots x_k$, the order-*j* ascending DD test statistic (which, in this paper, is also called the DD test statistic for the risk-averse or ADDj), $T_j^A(x)$ (j = 1, 2 and 3), is given by:

$$T_j^A(x) = \frac{\hat{F}_j^A(x) - \hat{G}_j^A(x)}{\sqrt{\hat{V}_j^A(x)}}, \tag{4}$$

where $\hat{V}_j^A(x) = \hat{V}_{F_j}^A(x) + \hat{V}_{G_j}^A(x) - 2\hat{V}_{FG_j}^A(x)$,

$$\hat{H}_j^A(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x-h_i)_+^{j-1},$$

$$\hat{V}_{H_j}^A(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-h_i)_+^{2(j-1)} - \hat{H}_j^A(x)^2\right], H = F, G; h = y, z;$$

$$\hat{V}_{FG_j}^A(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-y_i)_+^{j-1}\left(x-z_i\right)_+^{j-1} - \hat{F}_j^A(x)\hat{G}_j^A(x)\right].$$

Because, empirically, it is impossible to test the null hypothesis for the full support of the distributions, Bishop et al. (1992) propose to test the null hypothesis for a pre-designed finite numbers of values of *x*. Specifically, the following hypotheses are tested:

$$\begin{aligned}
&H_0 : F_j^A(x_i) = G_j^A(x_i)\ , \text{ for all } x_i,\ i = 1,2,...,k;\\
&H_A : F_j^A(x_i) \neq G_j^A(x_i) \text{ for some } x_i \text{ but } F \nsucc G, F \nprec G;\\
&H_{A1} : F_j^A\left(x_i\right) \leq G_j^A\left(x_i\right) \text{ for all } x_i \text{ and } F_j^A\left(x_i\right) < G_j^A\left(x_i\right) \text{ for some } x_i;\\
&H_{A2} : F_j^A\left(x_i\right) \geq G_j^A\left(x_i\right) \text{ for all } x_i \text{ and } F_j^A\left(x_i\right) > G_j^A\left(x_i\right) \text{ for some } x_i;
\end{aligned} \tag{5}$$

where the integrals F_j^A and G_j^A are defined as in (1) for $j = 1,2,3$ and $F \nsucc G$ means *F* does not dominate *G* and vice versa. It should be noted that in the above hypotheses, H_A is set to be exclusive of both H_{A1} and H_{A2}, meaning that if the test accepts H_{A1} or H_{A2}, it will not classify them as H_A. Under the null hypothesis, DD show that $T_j^A\left(x\right)$ is asymptotically distributed as the studentized maximum modulus (SMM) distribution (Richmond, 1982) to account for joint test size. To implement the DD test, the t-statistic, T_j^A, at each grid point is computed. The null hypothesis, H_0, is rejected if T_j^A is significant at any grid point. The SMM distribution with *k* and infinite degrees of freedom at the α% significance level, denoted by $M_{\infty,\alpha}^k$, is used to control for the probability of rejecting the null hypothesis. The following decision rules are adopted based on a 1-α percentile of $M_{\infty,\alpha}^k$ tabulated by Stoline and Ury (1979):

$$\begin{array}{l}\text{If } \left|T_j^A(x_i)\right| < M_{\infty,\alpha}^k \text{ for } i = 1,...,k, \text{ accept } H_0; \\ \text{if } T_j^A(x_i) < M_{\infty,\alpha}^k \text{ for all } i \text{ and } -T_j^A(x_i) > M_{\infty,\alpha}^k \text{ for some } i, \text{ accept } H_{A1}; \\ \text{if } -T_j^A(x_i) < M_{\infty,\alpha}^k \text{ for all } i \text{ and } T_j^A(x_i) > M_{\infty,\alpha}^k \text{ for some } i, \text{ accept } H_{A2}; \text{ and} \\ \text{if } T_j^A(x_i) > M_{\infty,\alpha}^k \text{ for some } i \text{ and } -T_j^A(x_i) > M_{\infty,\alpha}^k \text{ for some } i, \text{ accept } H_A. \end{array} \quad (6)$$

Accepting either H_0 or H_A implies that no SD exists between the returns of any two assets, no arbitrage opportunity exists between these two assets, and neither of these two assets is preferred to the other. However, if H_{A1} (H_{A2}) of order one is accepted, asset F (G) stochastically dominates G (F) at first order. From this perspective, an arbitrage opportunity exists and any non-satiated investor will be better off if he/she switches from the dominated asset to the dominant one. On the other hand, if H_{A1} or H_{A2} is accepted for order two or three, a particular investment stochastically dominates the other at second or third order. In this situation, an arbitrage opportunity does not exist, and switching from one asset to another will increase only investors' expected utilities but not their wealth (Jarrow, 1986; Falk and Levy 1989).

The DD test is designed to compare the distributions at a finite number of grid points. Too few grids will miss information of the distributions between any two consecutive grids (Barrett and Donald, 2003); however, too many grids will violate the independence assumption required by the SMM distribution (Richmond, 1982). Various studies examine the choice of grid points. For instance, Tse and Zhang (2004) show that an appropriate choice of *k* for reasonably large samples ranges from 6 to 15. To make more detailed comparisons without violating the independence assumption, we follow Fong et al. (2005) and Gasbarro et al. (2007) to make 10 major partitions with 10 minor partitions within any two consecutive major partitions in each comparison and to make the statistical inference based on the SMM distribution for *k* =10 and infinite degrees of freedom.[5] This allows us to examine the consistency of both magnitudes and signs of the DD statistics between any two consecutive major partitions.

[5] Refer to Lean et al. (2006) for the reasoning. Critical values are 3.691, 3.254 and 3.043 for the 1%, 5%, and 10% levels of significance tabulated in Stoline and Ury (1979).

Having stated the procedure for the ascending DD test statistics, we shall consider the order-*j* descending DD test for the risk-seekers. The order-*j* descending DD test statistic (which, in this paper, is also called the DD test statistic for the risk-seekers or DDDj), $T_j^D(x)$ (*j* = 1, 2 and 3), is expressed by:

$$T_j^D(x) = \frac{\hat{F}_j^D(x) - \hat{G}_j^D(x)}{\sqrt{\hat{V}_j^D(x)}}, \qquad (7)$$

where $\hat{V}_j^D(x) = \hat{V}_{F_j}^D(x) + \hat{V}_{G_j}^D(x) - 2\hat{V}_{FG_j}^D(x)$,

$$\hat{H}_j^D(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(h_i - x)_+^{j-1},$$

$$\hat{V}_{H_j}^D(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(h_i - x)_+^{2(j-1)} - \hat{H}_j^D(x)^2\right], H = F, G; h = y, z;$$

$$\hat{V}_{FG_j}^D(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(y_i - x)_+^{j-1}\left(z_i - x\right)_+^{j-1} - \hat{F}_j^D(x)\hat{G}_j^D(x)\right];$$

in which the integrals F_j^D and G_j^D are defined as in (1) for $j = 1, 2, 3$. The decision rules for risk-seekers can be obtained from modifying (6) as follows:

$H_0 : F_j^D(x_i) = G_j^D(x_i)$, for all x_i, $i = 1, 2, ..., k$;
$H_D : F_j^D(x_i) \neq G_j^D(x_i)$ for some x_i but $F \not\succ G, F \not\prec G$;
$H_{D1} : F_j^D\left(x_i\right) \geq G_j^D\left(x_i\right)$ for all x_i and $F_j^D\left(x_i\right) > G_j^D\left(x_i\right)$ for some x_i;
$H_{D2} : F_j^D\left(x_i\right) \leq G_j^D\left(x_i\right)$ for all x_i and $F_j^D\left(x_i\right) < G_j^D\left(x_i\right)$ for some x_i;

and the following decision rules are adopted for risk-seekers:

If $\left|T_j^D(x_i)\right| < M_{\infty,\alpha}^k$ for $i = 1, ..., k$, accept H_0;
if $-T_j^D(x_i) < M_{\infty,\alpha}^k$ for all i and $T_j^D(x_i) > M_{\infty,\alpha}^k$ for some i, accept H_{D1};
if $T_j^D(x_i) < M_{\infty,\alpha}^k$ for all i and $-T_j^D(x_i) > M_{\infty,\alpha}^k$ for some i, accept H_{D2}; and
if $T_j^D(x_i) > M_{\infty,\alpha}^k$ for some i and $-T_j^D(x_i) > M_{\infty,\alpha}^k$ for some i, accept H_D.

As in the case of the test for the risk-averse, accepting either H_0 or H_D implies that no SD exists between *F* and *G*, no arbitrage opportunity exists between these two markets, and neither of these assets is preferred to the other. If H_{D1} (H_{D2}) of order one is accepted, asset F (G) stochastically dominates G (F) at first order. In this situation, an arbitrage opportunity exists, and any non-satiated investor will be better off if he/she switches from the dominated asset to the dominant one. On the other hand, if H_{D1} or H_{D2} is accepted for order two or three, a particular asset stochastically dominates the other at second or third order. In this situation, an arbitrage opportunity does not exist, and switching from one asset to another will increase only the risk-seekers' expected utility but their not wealth.

4. EMPIRICAL RESULTS AND DISCUSSIONS

While we are primarily interested in the results of the SD test, for comparative purposes, we first apply the MV criterion and display a summary of its descriptive statistics of the data in this study in Table 1. All assets gain, on average, positive daily returns. The REITs and Treasury bill and Treasury note are statistically significant (greater than zero) but not the stock returns. The daily mean returns on REITs are 0.04% - 0.06%, much higher than the daily mean returns of other asset groups. Consistent with the common intuition, based on daily returns, REITs outperformed the stock indices and Treasury constant maturities for the period under study. However, the unreported pairwise t-tests show that only all REITs and equity REITs are significantly different from the S&P 500 and the two Treasury constant maturities at the 5% level. REITs also exhibit a smaller standard deviation than that of the three stock indices, but they have a larger standard deviation than the Treasury constant maturities. Applying the MV criterion, we find that all REITs (except mortgage REITs) dominate the three stock indices but not the Treasury constant maturities. Mortgage REITs dominate the NASDAQ only by the MV criterion.[6]

Insert Table 1

As shown in Table 1, the highly significant Jarque-Bera statistics suggest that the

[6] The statistics are available on request.

return distributions for all assets are non-normal. The evidence further indicates that all assets have significant skewness and kurtosis. REITs exhibit negative skewness, and mortgage REITs have a very high kurtosis (59.22). The exhibition of significant skewness and kurtosis further supports the non-normality of return distributions. Moreover, on the basis of the findings using the MV criterion, we cannot conclude whether investors' preferences between assets will lead to an increase in wealth or, in the case of risk-averse or risk-seeking individuals, whether their preferences will increase their expected utility. However, the SD approach allows us to address the issue. To demonstrate the use of the SD approach, we first plot the cumulative distribution functions of returns on equity REITs and the S&P 500 in Figure 1 and plot the CDFs of returns on equity REITs and the 3-month Treasury bill in Figure 2 as examples. The plots show that there is no FASD between any two pairs of returns as their CDFs cross.[7]

Insert Figs. 1 & 2

Figure 1 also shows the ascending DD statistics, T_j^A ($j = 1, 2, 3$), over the entire distribution of returns for equity REITs and the S&P 500. This figure provides a visual representation of the DD test results. In particular, T_1^A moves from negative to positive along the distribution of returns. This implies that equity REITs dominate the S&P 500 in the downside risk (negative returns), while the S&P 500 dominates equity REITs in the upside profit (positive returns). To compare equity REITs with the 3-month Treasury bill, in Figure 2 we plot the ascending DD statistics for these two asset returns. The DD statistics show different movements from those in Figure 1. We find that equity REITs are dominated by the 3-month Treasury bill in the downside risk and the dominance order reverses in the upside profit.

However, the DD statistics could be significant or insignificant based on the critical values of SMM distributions. The rule set by the DD test states that the null hypothesis

[7] The plots of other pairs also reveal no FASD. The results are available on request.

can be rejected if any of the t-statistics defined in (4) (or (5)) are significantly different from zero. To minimize the type II error of dominance and to accommodate the effect of almost SD (Leshno and Levy, 2002), we use a conservative 5% cut-off point for the proportion of t-statistics for statistical inference. Using a 5% cut-off point as a benchmark, for the risk-averse, if REITs dominate any of the other assets, we should find at least 5% significantly negative j-order ascending DD statistics, T_j^A, and no significantly positive T_j^A statistics. The reverse holds if REITs are dominated by any of the other assets. On the other hand, for risk-seekers, if REITs dominate any of the other assets, we should find at least 5% significantly positive j-order descending DD statistics, T_j^D, and no significantly negative T_j^D statistics. The reverse holds if REITs are dominated by any of the other assets.

Insert Table 2

Table 2 shows the results of the DD test for risk-averters for the entire period. There are four groups showing a pairwise comparison between four types of REITs and other assets.[8] We take the pair of equity REITs and the S&P 500 as examples. The evidence from Table 2 suggests that 21% of T_1^A is significantly negative, and 24% of T_1^A is significantly positive for the risk-averse. This implies no FASD between the pair of equity REITs and the S&P 500. We find similar results for all the other pairs, such as equity REITs and Dow Jones Industrials and equity REITs and the NASDAQ.

All T_2^A and T_3^A for the comparison of equity REITs and the S&P 500 are negative along the distribution of returns as shown in Figure 1. In addition, Table 2 shows that 34% of T_2^A and 58% of T_3^A are found to be significantly negative at the 5% level. Thus, we conclude that equity REITs dominate the S&P 500 at second and

[8] The results of the comparison of other pairs are available on request.

third order under ASD, implying that any risk-averse investor would prefer equity REITs to the S&P 500 for maximizing utility. On the other hand, for the comparison of equity REITs and the 3-month Treasury bill (and 10-year Treasury note), we find that 23% of T_1^A is significantly negative and 32% of T_1^A is significantly positive for risk-averters. Further inspecting the DD statistics for the second and third order for risk-averters, we see that the 3-month Treasury bill (10-year Treasury note) dominates equity REITs, since 34% of T_2^A and 48% (50%) of T_3^A are found to be significantly positive at the 5% level.

Overall, evidence derived from ascending DD statistics indicates there is no FASD between REITs and other assets, suggesting that investors cannot increase their wealth by switching from one asset to the other and there is no arbitrage opportunity between them (Bawa, 1978; Jarrow, 1986). These results are also evidence that we cannot reject market efficiency. However, by considering the statistics from SASD and TASD, we can determine whether investors could increase their expected utility by switching from one asset to another. In our research, it is apparent that risk-averters prefer REITs (except mortgage REITs) to stocks, while they prefer Treasury constant maturities over REITs for maximizing their expected utility. This implies that they will increase their expected utility by switching their investments from stocks to real estate and from real estate to fixed-income assets.

Insert Figs. 3 & 4

Figures 3 and 4 present the cases for the descending CDF and the corresponding descending DD statistics for equity REITs and the S&P 500 and equity REITs and the 3-month Treasury bill, respectively. Specifically, Figure 3 reveals that the T_1^D is negative in the upside return region and positive in the downside return region, revealing that the S&P 500 is preferred to equity REITs in the upper range of returns and vice versa.

On the other hand, Figure 4 shows the descending CDF and the corresponding descending DD statistics for equity REITs and the 3-month Treasury bill, respectively. Figure 4 reveals that the T_1^D is negative in the downside return region and positive in the upside return region. Putting the information together, it is clear that the 3-month Treasury bill is preferred to equity REITs in the lower range of returns and the reverse is true in the upper range based on FDSD.

Insert Table 3

Table 3 reports the descending DD statistics for risk-seekers. As in Table 2, taking the comparison of equity REITs and the S&P 500 as an example, we find that 33% of T_2^D and 39% of T_3^D are negative and statistically significant, respectively. Hence, risk-seeking investors will unambiguously prefer the S&P 500 to equity REITs to maximize their expected utility. On the other hand, if we compare equity REITs and the 3-month Treasury bill, risk-seeking investors will prefer equity REITs to the 3-month Treasury bill as is evident from the fact that 45% of T_2^D and 66% of T_3^D are positive and statistically significant, respectively. Different from the evidence for risk-averters, evidence from second- and third-order T_j^D statistics reveals that risk-seekers will increase their expected utility by switching from real estate to stocks and from fixed-income assets to real estate.

Is there time-varying behavior for risk-averters and risk-seekers? Dynamic asset price movements suggest that asset returns are subject to ongoing external shocks in addition to some big events and extraordinary economic/social disturbances. It is of interest to examine whether investors' behavior is influenced by the up and down market trend. To address this issue, we divided the entire sample into two sub-periods. That is, we treat the period from January 1999 to December 2002 as an up market and

January 2003 to December 2005 as a down market. This allows us to investigate the behavioral differential conditioned on the financial economic environment.

Insert Table 4

The results for the two sub-periods are presented in Table 4. As we reported earlier, there is no FSD among all assets studied in this paper for each sub-period, implying that an arbitrage opportunity does not exist among these assets in both bull and bear markets. On the other hand, REITs are found to be dominated by Treasury constant maturities under ASD, while REITs dominate Treasury constant maturities under DSD in both sub-periods, indicating that investors' behavior concerning fixed-income assets are not influenced by economic conditions. Nevertheless, we observe substantial differences among the distributions of other assets during different time periods. For instance, except for mortgage REITs, all other REITs are found to dominate stock indices under ASD in sub-period 1 but not in sub-period 2. For DSD, we find a change in direction of preference from sub-period 1 to sub-period 2. In particular, the S&P 500 dominates equity REITs in sub-period 1; however, it is dominated by equity REITs in sub-period 2 under DSD, implying that investors' behavior concerning stocks could be time-varying and influenced by market conditions.

5. CONCLUSION

It is a widely accepted stylized fact that returns on most financial assets exhibit leptokurtosis and sometimes asymmetry and they are not normally distributed (Peiró, 1999; Patton, 2004; Brooks, et al., 2005). The parametric analysis derived from the MV approach is likely to be misleading or of limited value. In addition, empirical findings using the MV approach cannot be used to decide whether investors' portfolio preferences will increase wealth or, in the case of risk-averse investors, lead to an increase in utility without an increase in wealth. Given the limitation of the MV approach and the lack of a clear solution to the fat-tail distributions, this study is based on the SD approach, which is not distribution-dependent, and can shed light on the utility and wealth implications of portfolio preferences by exploiting information obtained from higher order moments to test their performance.

By investigating the data on REITs and five other assets over the entire sample period of 1999–2005, we find that all REITs (except mortgage REITs) dominate the three stock indices but not the Treasury constant maturities using the MV criterion. We also find no FSD between them. This implies that investors cannot increase their wealth by switching from one asset to another. However, REITs (except mortgage REITs) stochastically dominate returns on the three stock indices but are stochastically dominated by fixed-income securities, the 3-month Treasury bill, and the 10-year Treasury bond at the second and third order for risk-averters. We find the reverse case for risk-seekers. This means that to maximize their expected utility, all risk-averse investors would prefer to invest in real estate than in the stock market, subject to trading costs. However, if we compare real estate to fixed-income assets, they would prefer fixed-income assets to real estate. On the other hand, all risk-seeking investors would prefer to invest in the stock market than in real estate (or in real estate rather than in fixed-income assets) to maximize their expected utility. In addition, we find that investors' behavior concerning fixed-income assets is not influenced by economic conditions, while their behavior concerning stocks is time-varying and influenced by market conditions.

Last, we note that SD is found to be important in risk measurement, since the first-order SD is found to be equivalent to the value-at-risk, while the second-order SD is found to be equivalent to the conditional value-at-risk (Ogryczak and Ruszczyński, 2002; Leitner, 2005; Ma and Wong, 2006). Thus, adopting SD for analysis will include inferences made by employing VaR and conditional VaR. We also note that if the prospects belong to the same local-scale family, the preference for the prospects drawn from the MV criterion will be the same as that drawn from the ascending SD criterion (Meyer, 1987; Wong and Ma, 2008). In addition, this paper extends the work on the SD test from risk-averters to risk-seekers. Further research could include extending our work to test the SD theory for investors with S-shaped and reverse S-shaped utility functions as developed by Levy and Wiener (1998), Levy and Levy (2004), Wong and Chan (2008), among others.

REFERENCES

Ambrose BW, Esther A, Griffiths MD. The fractal structure of real estate investment trust returns: The search for evidence of market segmentation and nonlinear dependency. Journal of the American Real Estate and Urban Economics Association 1992; 20; 25-54.

Anderson G.,1996. Nonparametric tests of stochastic dominance in income distributions. Econometrica 64, 1183–1193.

Anderson G.., 2004. Toward an empirical analysis of polarization. Journal of Econometrics122; 1-26.

Anderson R. I., Lewis D, Springer, T.M., 2000. Operating efficiencies in real estate: A critical review of the literature. Journal of Real Estate Literature 8, 3-18.

Barrett G., Donald S. 2003. Consistent tests for stochastic dominance. Econometrica 71 71-104.

Bawa V.S., 1978. Safety-first, stochastic dominance, and optimal portfolio choice. Journal of Financial and Quantitative Analysis 13 255-271.

Bernard V.L., Seyhun H.N., 1997. Does post-earnings-announcement drift in stock prices reflect a market inefficiency? A stochastic dominance approach. Review of Quantitative Finance and Accounting 9, 17-34.

Bharati R, Gupta M., 1992. Asset allocation and predictability of real estate returns. Journal of Real Estate Research 7, 469-84.

Bishop J.A, Formly, J.P, Thistle P.D., 1992. Convergence of the south and non-south income distributions. American Economic Review 82, 262-272.

Brooks C, Burke SP, Heravi S, Persand G.. Autoregressive conditional kurtosis. Journal of Financial Econometrics 2005; 3, 399-421.

Cheng P., 2005. Asymmetric risk measures and real estate returns. Journal of Real Estate Finance and Economics 30, 89–102.

Cheng P, Wolverton, L. M., 2001. MPT and the downside risk framework: A comment on two recent studies. Journal of Real Estate Portfolio Management 7, 125-131.

Chiang, K.C.H., Lee, M.L., Wisen, C.H.., 2005. On the time-series properties of real estate investment trust betas. Real Estate Economics 33, 381–396.

Chui, A.C.W., Titman, S., Wei, K.C.J., 2003, The cross section of expected REIT returns. Real Estate Economics 3, 451-479.

Colwell P.F., Park, H.Y., 1990. Seasonality and size effects: The case of real-estate related investment. Journal of Real Estate Finance and Economics 3, 251-59.

Davidson, R,, Duclos, J.Y., 2000. Statistical inference for stochastic dominance and for the measurement of poverty and inequality. Econometrica 68, 1435-1464.

Enders, W.,1995. Applied econometric time series. New York: John Wiley:

Falk, H., Levy, H., 1989, Market reaction to quarterly earnings' announcements: A stochastic dominance based test of market efficiency. Management Science 35, 425-446.

Feldstein, M.S. 1969. Mean variance analysis in the theory of liquidity preference and portfolio selection. Review of Economics Studies 36, 5-12.

Firstenberg, P., Ross, S., Zisler, R., 1988. Real estate: The whole story. Journal of Portfolio Management 14, 22-34.

Fishburn, P.C., 1964. Decision and value theory. New York: John Wiley.

Fong, W.M, Wong W.K, Lean, H.H., 2005. International momentum strategies: A stochastic dominance approach. Journal of Financial Markets 8, 89–109.

Gasbarro, D., Wong, W.K, Zumwalt, J.K., 2007. Stochastic dominance analysis of ishares. European Journal of Finance 13, 89-101.

Goldstein, A., Nelling, E.F., 1999. REIT return behavior in advancing and declining stock markets. Real Estate Finance 15, 68-77.

Hakansson, N., 1972. Mean variance analysis in a finite world. Journal of Financial and Quantitative Analysis 7, 1873-1880.

Hammond, J.S., 1974. Simplifying the choice between uncertain prospects where preference is nonlinear. Management Science 20,1047-1072.

Hanoch, G.., Levy, H., 1969. The efficiency analysis of choices involving risk. Review of Economic Studies 36, 335-346.

Harvey, C.R., Siddique A., 2000.Conditional skewness in asset pricing tests. Journal of

Finance 55, 1263.

Jarrow, R., 1986. The relationship between arbitrage and first order stochastic dominance. Journal of Finance 41, 915-921.

Jirasakuldech, B., Knight, J.R., 2005. Efficiency in the market for REITs: Further evidence. Journal of Real Estate Portfolio Management 11,123-132.

Kaur, A., Rao, B.L.S.P, Singh, H., 1994. Testing for second order stochastic dominance of two distributions. Econometric Theory 10, 849-866.

Khoo, T., Hartzell, D., Hoesli, M., 1993. An investigation of the change in real estate investment trust betas. Journal of American Real Estate and Urban Economics Association 21, 107–130.

Kjetsaa, R., Kieff, M., 2003. Stochastic dominance analysis of equity mutual fund performance. American Business Review 21, 1-8.

Klecan, L., McFadden, R., McFadden, D., 1991. A robust test for stochastic dominance. Working Paper MIT & Cornerstone Research.

Kleiman, R.T., Payne, J.E., Sahu, A.P., 2002. Random walks and market efficiency: Evidence from international real estate markets. Journal of Real Estate Research 24, 279-96.

Kuhle, J.L., Alvayay, J.R., 2000. The efficiency of equity REIT prices. Journal of Real Estate Portfolio Management 6, 349-54.

Larsen, G..A., Resnick, B.G.., 1999. A performance comparison between cross-sectional stochastic dominance and traditional event study methodologies. Review of Quantitative Finance and Accounting 12, 103-112.

Lean, H.H., Wong, W.K., Zhang, X. ,2006. Size and power of some stochastic dominance tests. SSRN Working Paper No. 880988.

Lee, S., Stevenson, S., 2005. The case for REITs in the mixed-asset portfolio in the short and long run. Journal of Real Estate Portfolio Management 11, 55-80.

Leitner, J., 2005. A short note on second-order stochastic dominance preserving coherent risk measures. Mathematical Finance 15, 649-651.

Leshno, M., Levy, H., 2002. Preferred by "all" and preferred by "most" decision makers: Almost stochastic dominance. Management Science 48, 1074-1085.

Levy, H., Wiener, Z., 1998. Stochastic dominance and prospect dominance with subjective weighting functions. Journal of Risk and Uncertainty 16, 147–163.

Levy, H., Levy, M., 2004. Prospect theory and mean-variance analysis. Review of Financial Studies 17, 1015-1041.

Li, C. K., Wong, W.K., 1999. A note on stochastic dominance for risk averters and risk takers. RAIRO Recherche Opérationnelle 33, 509-524.

Li, Y., Wang, K., 1995. The predictability of REIT returns and market segmentation. Journal of Real Estate Research 10, 471-82.

Ling, D., Naranjo, A., 2003. The dynamics of REIT capital flows and returns. Real Estate Economics 31, 405-434.

Linton, O., Maasoumi, E., Whang, Y.J., 2005. Consistent testing for stochastic dominance under general sampling schemes. Review of Economic Studies 72, 735-765.

Liu, C., Hartzell, D., Greig, W., Grissom, T., 1990, The integration of the real estate market and the stock market: Some preliminary evidence. Journal of Real Estate Finance and Economics 3, 261-282.

Liu, C., Hartzell, D. J.,. Grissom T.V., 1992. The role of co-skewness in the pricing of real estate. Journal of Real Estate Finance and Economics 5, 299-319.

Liu, C.H., Mei, J., 1992. The predictability of returns on equity REITs and their co-movement with other assets. Journal of Real Estate Finance and Economics 5, 401-418.

Loretan, M., Phillips, P.C.B., 1994. Testing the covariance stationarity of heavy-tailed time series: An overview of the theory with applications to several financial data series. Journal of Empirical Finance 211-248.

Ma, C., Wong, W.K., 2006. Stochastic dominance and risk measure: A decision-theoretic foundation for VaR and C-VaR. Working Paper, University of Essex.

McDonald, J.B., Xu, Y. J., 1995. A generalization of the beta distribution with applications. Journal of Econometrics 66, 133-152.

McFadden, D., 1989. Testing for Stochastic Dominance. In: Fomby, T.B., Seo, T.K., (Eds), Studies in the economics of uncertainty. New York: Springer Verlag.

McIntosh, W., Liang, Y., Tompkins, D.L., 1991. An examination of the small firm effect within the REIT industry. Journal of Real Estate Research 6, 9–18.

Meyer, J., 1977. Second degree stochastic dominance with respect to a function. International Economic Review 18, 476-487.

Meyer, J., 1987. Two-moment decision models and expected utility maximization. American Economic Review 77, 421-430.

Nelling, E., Gyourko, J., 1998. The predictability of equity REIT returns. Journal of Real Estate Research 3, 251-268.

Ogryczak, W., Ruszczyński, A., 2002. Dual stochastic dominance and related mean-risk models. SIAM Journal of Optimization 13, 60-78.

Patton, A.J., 2004. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. Journal of Financial Econometrics 2, 130-168.

Peiró, A., 1999. Skewness in financial returns. Journal of Banking and Finance 6, 847-862.

Peterson, J.D., Hsieh, C., 1997. Do common risk factors in the returns on stocks and bonds explain returns on REITs? Real Estate Economics 25, 321-345.

Porter, R.B., Gaumnitz, J.E., 1972. Stochastic dominance vs. mean-variance portfolio analysis: An empirical evaluation. American Economic Review 62, 438-446.

Quirk, J.P., Saposnik, R., 1962. Admissibility and measurable utility functions. Review of Economic Studies 29, 140-146.

Richmond, J., 1982. A general method for constructing simultaneous confidence intervals. Journal of the American Statistical Association 77, 455-460.

Sagalyn, L., 1990. Real estate risk and the business cycle: Evidence from security markets. Journal of Real Estate Research 5, 203-219.

Seck, D., 1996. The substitutability of real estate assets. Real Estate Economics 24, 75-95.

Seyhun, H.N., 1993. Can omitted risk factors explain the January effect? A stochastic dominance approach. Journal of Financial and Quantitative Analysis 28,195-212.

Shalit, H., Yitzhaki, S., 2002. Estimating Beta. Review of Quantitative Finance and Accounting 18, 95-118.

Sing, T.F., Ong, S.E., 2000. Asset allocation in a downside risk framework. Journal of Real Estate Portfolio Management 6, 213-224.

Sivitanides, P.S., 1998. A downside risk approach to real estate portfolio structuring. Journal of Real Estate Portfolio Management 4, 159-168.

Smith, D., 2007. Conditional coskewness and asset pricing. Journal of Empirical Finance 14, 91-119.

Stoline, M.R., Ury, H.K., 1979. Tables of the studentized maximum modulus distribution and an application to multiple comparisons among means. Technometrics 21,87-93.

Stoyan, D., 1983. Comparison methods for queues and other stochastic models. New York: John Wiley.

Swanson, Z., Theis, J., Casey, K.M., 2002. REIT risk premium sensitivity and interest rates. Journal of Real Estate Finance and Economics 24, 319-330.

Tse, Y.K., Zhang, X., 2004. A Monte Carlo investigation of some tests for stochastic dominance. Journal of Statistical Computation and Simulation 74, 361-378.

Vines, T.W., Hsieh, C.H., Hatem, J.J., 1994. The role of systematic covariance and co-skewness in the pricing of real estate: Evidence from equity REITs. Journal of Real Estate Research 9, 421-429.

Vinod, H.D., 2004. Ranking mutual funds using unconventional utility theory and stochastic dominance. Journal of Empirical Finance 11, 353–377.

Wong,W.K., Chan, R., 2008. Markowitz and prospect stochastic dominances. Annals of Finance 4(1), 105-129.

Wong, W.K., Li, C.K. 1999.A note on convex stochastic dominance theory. Economics Letters 62, 293-300.

Wong, W.K, Ma, C., 2008. Preferences over location-scale family. Economic Theory 37(1), 119-146.

Table 1. A Summary of Descriptive Statistics for Various Asset Returns (1999–2005)

Asset	Mean	Std. Dev.	Skewness	Kurtosis	J-B
All REIT (ART)	0.05973***	0.8168	-0.3653***	3.8280***	1154.88***
Equity REIT (ERT)	0.06148***	0.8242	-0.3427***	3.7216***	1088.93***
Mortgage REIT (MRT)	0.06181*	1.4140	1.2879***	59.217***	267156***
US-DS Real Estate (DRE)	0.03554*	0.8860	-0.1792***	3.2354***	805.78***
Dow Jones Industrials (DJI)	0.01451	1.0998	0.1974***	2.6265***	536.40***
NASDAQ (NAS)	0.01927	1.9509	0.3173***	3.5756***	1002.80***
S&P 500 (SP5)	0.00741	1.1473	0.2208***	2.0591***	337.24***
10-Year T. Note (TB10)	0.01326***	0.00218	0.4603***	-0.7526***	107.52***
3-Month T. Bill (TB3)	0.008208***	0.00477	0.3640***	-1.2980***	168.53***

Notes:

Skewness (SK) = E($R_{i,t} - \mu)^3 / \sigma^3$, where μ is the mean and σ is the standard deviation. Kurtosis (KUR) = E($R_{i,t} - \mu)^4 / \sigma^4$ .The asymptotic standard errors of SK and KUR are computed as $(6/T)^{0.5}$ and $(24/T)^{0.5}$, respectively. JB denotes Jarque-Bera statistic for testing normality defined by $T[SK^2/6 + (KUR-3)^2/24]$, which is asymptotically distributed as χ^2 (2). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Results of DD Test for Risk-Averters (1999–2005)

	FASD				SASD				TASD			
	% DD>0	% DD>CV	% DD<0	% DD<CV	% DD>0	% DD>CV	% DD<0	% DD<CV	% DD>0	% DD>CV	% DD<0	% DD<CV
ART - DJI	53	18	47	18	0	0	100	27	0	100	100	59
ART - NAS	59	27	41	23	0	0	100	32	0	100	100	74
ART - SP5	49	27	51	20	0	0	100	34	0	100	100	58
ART - TB10	53	30	47	23	63	33	37	0	100	48	0	0
ART - TB3	53	30	47	23	63	33	37	0	100	46	0	0
ERT - DJI	52	17	48	17	0	0	100	27	0	0	100	59
ERT - NAS	59	27	41	23	0	0	100	33	0	0	100	74
ERT - SP5	49	24	51	21	0	0	100	34	0	0	100	58
ERT - TB10	52	32	48	23	62	34	38	0	100	50	0	0
ERT - TB3	52	32	48	23	61	34	39	0	100	48	0	0
MRT - DJI	38	4	62	3	42	4	58	0	57	1	43	0
MRT - NAS	47	13	53	10	29	1	71	12	35	1	65	19
MRT - SP5	43	5	57	3	41	3	59	0	52	1	48	0
MRT - TB10	41	12	59	10	46	11	54	0	92	15	8	0
MRT - TB3	41	12	59	10	45	11	55	0	87	15	13	0
DRE - DJI	54	9	46	15	0	0	100	20	0	0	100	28
DRE - NAS	59	28	41	22	0	0	100	30	0	0	100	64
DRE - SP5	54	21	46	18	2	0	98	25	1	0	99	45
DRE - TB10	53	31	47	26	69	35	31	0	100	62	0	0
DRE - TB3	53	31	47	26	67	35	33	0	100	59	0	0

Notes: The table reports the percentages of positive and negative DD statistics, T_j^A (see eqn (4) for j = 1, 2, 3) for risk-averters, and their significant portions at the 5% significance level, based on the asymptotic critical value of 3.254 of the studentized maximum modulus (SMM) distribution.

ERT is equity REIT, MRT is mortgage REIT, and DRE is US-DS Real Estate.

ART - DJI means pairwise comparison of all REITs with the Dow Jones Industrial index. Other pairs are defined accordingly.

Table 3: Results of DD Test for Risk-Seekers (1999–2005)

	FDSD				SDSD				TDSD			
	% DD>0	% DD>CV	% DD<0	% DD<CV	% DD>0	% DD>CV	% DD<0	% DD<CV	% DD>0	% DD>CV	% DD<0	% DD<CV
ART - DJI	41	18	59	18	38	0	62	25	0	0	100	31
ART - NAS	41	23	59	27	27	0	73	30	0	0	100	47
ART - SP5	39	20	61	27	41	0	59	33	0	0	100	41
ART - TB10	47	23	53	30	100	40	0	0	100	67	0	0
ART - TB3	47	23	53	30	100	44	0	0	100	67	0	0
ERT - DJI	44	17	56	17	39	0	61	24	1	0	99	29
ERT - NAS	41	24	59	27	27	0	73	30	0	0	100	47
ERT - SP5	39	21	61	24	41	0	59	33	0	0	100	39
ERT - TB10	48	23	52	32	100	41	0	0	100	66	0	0
ERT - TB3	48	23	52	32	100	45	0	0	100	66	0	0
MRT - DJI	62	3	38	4	100	3	0	0	100	0	0	0
MRT - NAS	41	10	59	13	76	0	24	10	51	0	49	3
MRT - SP5	56	3	44	5	100	1	0	0	100	0	0	0
MRT - TB10	59	10	41	12	100	11	0	0	100	33	0	0
MRT - TB3	59	10	41	12	100	12	0	0	100	36	0	0
DRE - DJI	38	15	62	9	35	0	65	20	0	0	100	24
DRE - NAS	35	18	65	21	38	0	62	28	0	0	100	34
DRE - SP5	47	26	53	31	38	0	62	28	0	0	100	34
DRE - TB10	47	26	53	31	100	33	0	0	100	68	0	0
DRE - TB3	47	26	53	31	100	34	0	0	100	68	0	0

Notes: The table reports the percentages of positive and negative DD statistics, T_j^D (see eqn (7) for j = 1, 2, 3) for risk-seekers and their significant portions at the 5% significance level, based on the asymptotic critical value of 3.254 of the studentized maximum modulus (SMM) distribution.

ERT is equity REIT, MRT is mortgage REIT, and DRE is US-DS Real Estate.

ART - DJI means pairwise comparison of all REITs with the Dow Jones Industrial index. Other pairs are defined accordingly.

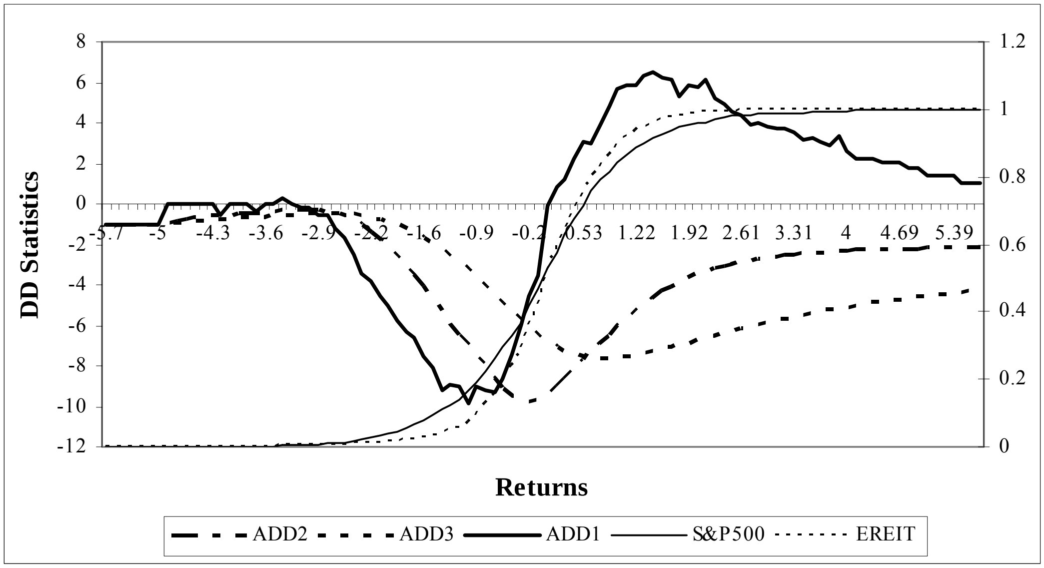
Table 4: Results of DD Test for Sub-periods

Sub-period 1 (1999 – 2002)		Sub-period 2 (2003 - 2005)	
Risk-Averters	Risk-Seekers	Risk-Averters	Risk-Seekers
ART $\succ_2$ DJI	ART $\prec^2$ DJI	ART $\nsucc$ DJI	ART $\succ^2$ DJI
ART $\succ_2$ NAS	ART $\prec^2$ NAS	ART $\nsucc$ NAS	ART $\prec^2$ NAS
ART $\succ_2$ SP5	ART $\prec^2$ SP5	ART $\nsucc$ SP5	ART $\succ^2$ SP5
ART $\prec_2$ TB10	ART $\succ^2$ TB10	ART $\prec_2$ TB10	ART $\succ^2$ TB10
ART $\prec_2$ TB3	ART $\succ^2$ TB3	ART $\prec_2$ TB3	ART $\succ^2$ TB3
ERT $\succ_2$ DJI	ERT $\prec^2$ DJI	ERT $\nsucc$ DJI	ERT $\succ^2$ DJI
ERT $\succ_2$ NAS	ERT $\prec^2$ NAS	ERT $\nsucc$ NAS	ERT $\prec^2$ NAS
ERT $\succ_2$ SP5	ERT $\prec^2$ SP5	ERT $\nsucc$ SP5	ERT $\succ^2$ SP5
ERT $\prec_2$ TB10	ERT $\succ^2$ TB10	ERT $\prec_2$ TB10	ERT $\succ^2$ TB10
ERT $\prec_2$ TB3	ERT $\succ^2$ TB3	ERT $\prec_2$ TB3	ERT $\succ^2$ TB3
MRT $\nsucc$ DJI	MRT $\nsucc$ DJI	MRT $\prec_2$ DJI	MRT $\succ^2$ DJI
MRT $\succ_2$ NAS	MRT $\prec^2$ NAS	MRT $\nsucc$ NAS	MRT $\nsucc$ NAS
MRT $\nsucc$ SP5	MRT $\nsucc$ SP5	MRT $\prec_2$ SP5	MRT $\succ^2$ SP5
MRT $\prec_2$ TB10	MRT $\succ^2$ TB10	MRT $\prec_2$ TB10	MRT $\succ^2$ TB10
MRT $\prec_2$ TB3	MRT $\succ^2$ TB3	MRT $\prec_2$ TB3	MRT $\succ^2$ TB3
DRE $\succ_2$ DJI	DRE $\prec^2$ DJI	DRE $\nsucc$ DJI	DRE $\succ^2$ DJI
DRE $\succ_2$ NAS	DRE $\prec^2$ NAS	DRE $\nsucc$ NAS	DRE $\prec^2$ NAS
DRE $\succ_2$ SP5	DRE $\prec^2$ SP5	DRE $\nsucc$ SP5	DRE $\succ^2$ SP5
DRE $\prec_2$ TB10	DRE $\succ^2$ TB10	DRE $\prec_2$ TB10	DRE $\succ^2$ TB10

DRE $\prec_2$ TB3	DRE $\succ^2$ TB3	DRE $\prec_2$ TB3	DRE $\succ^2$ TB3

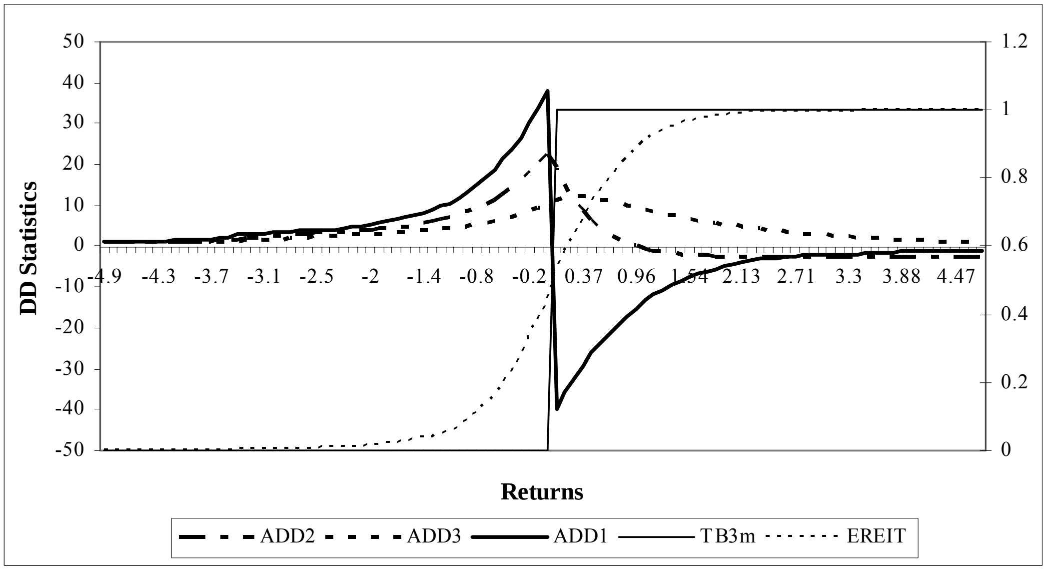
Notes: $Y \succ_j \left(\prec_j\right) Z$ means Y dominates (is dominated by) Z under order-j ASD (refer to (2)) and $Y \succ^j \left(\prec^j\right) Z$ means Y dominates (is dominated by) Z under order-j DSD (refer to (3)) respectively for j = 1, 2 and 3. Y $\nsucc$ Z means no SD between Y and Z (refer to (5)).

Figure 1: CDF and DD Statistics Between Equity REITs and the S&P 500 for Risk-Averters



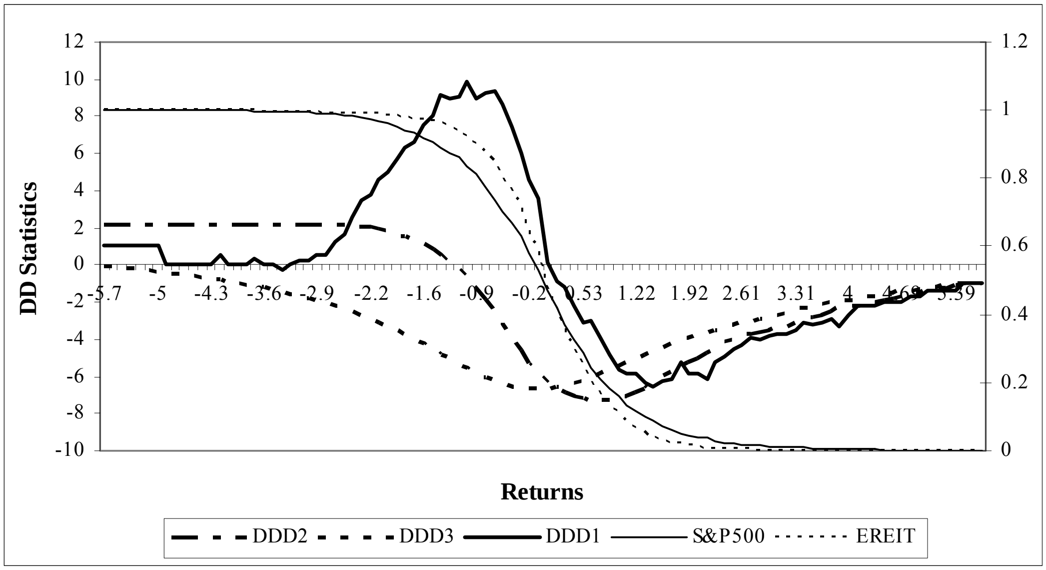
Note: CDF is defined in (1) and the order-j DD Statistic, T_j^A (ADDj), for risk-averters is defined in (4) for j = 1, 2 and 3.

Figure 2: CDF and DD Statistics Between Equity REITs and 3-Month T. Bill for Risk-Averters



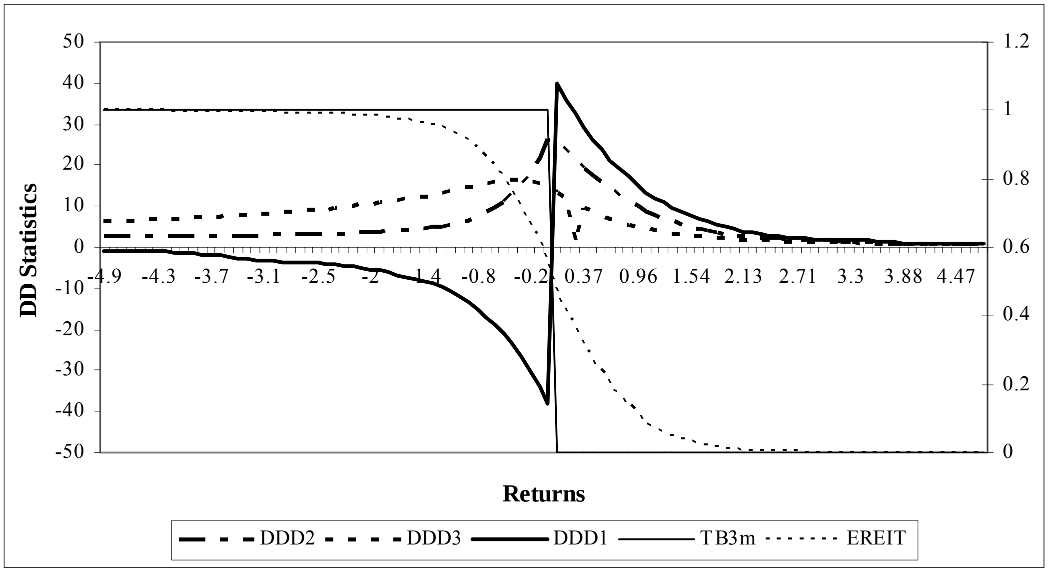
Note: CDF is defined in (1) and the order-j DD Statistic, T_j^A (ADDj), for risk-averters is defined in (4) for j = 1, 2 and 3.

Figure 3: Descending CDF and DD Statistics Between Equity REITs and the S&P 500 for Risk-Seekers



Note: Descending CDF is defined in (1) and the order-j DD Statistic, T_j^D (DDDj), for risk-seekers is defined in (7) for j = 1,2 and 3.

Figure 4: Descending CDF and DD Statistics Between Equity REITs and 3-Month T. Bill for Risk-Seekers



Note: Descending CDF is defined in (1) and the order-j DD Statistic, T_j^D (DDDj), for risk-seekers is defined in (7) for j = 1,2 and 3.

EFFECTIVE BASEMETAL HEDGING: THE OPTIMAL HEDGE RATIO AND HEDGING HORIZON

Michaël Dewally
Marquette University

Luke Marriott
MillerCoors

ABSTRACT

This study investigates optimal hedge ratios in all base metal markets. Using recent hedging computation techniques, we find that 1) the short-run optimal hedging ratio is increasing in hedging horizon, 2) that the long-term horizon limit to the optimal hedging ratio is not converging to one but is slightly higher for most of these markets, and 3) that hedging effectiveness is also increasing in hedging horizon. When hedging with futures in these markets, one should hedge long-term at about 6 to 8 weeks with a slightly greater than one hedge ratio. These results are of interest to many purchasing departments and other commodity hedgers.

I. INTRODUCTION

Hedging is considered an integral part of a competitive and successful commodity purchasing department. With raw material demand rising globally the strategic importance of hedging has never been as critical as it is today. Volatility in commodity markets continues to increase because of 1) political uncertainty and natural disasters, 2) the expanding global nature of trade and the resulting soaring demands from remote markets, and 3) a corresponding shift in manufacturing capacity as more product flow into the U.S. from abroad (Dickson et al. (2006)). Due to the increased volatility in commodity markets and strengthened global competition, companies can no longer rely on traditional approaches, such as strategic sourcing and volume aggregation, to manage their purchasing needs. Multinational firms no longer compete "…by exploiting scale and scope economies or by taking advantage of imperfections in the world's goods, labor, and capital markets" (Hansen and Nohria (2004)). Firms must rely more than before on risk management techniques to manage their materials exposure. These techniques include, but are not limited to, eliminating cost inefficiencies in operations, hedging commodity price risk with financial derivatives, and altering hedging horizons.

Our study concentrates on optimal hedging ratios and horizons in the metals markets. Our results show that 1) the short-run optimal hedging ratio is increasing in hedging horizon, 2) the long-term horizon limit to the optimal hedging ratio is not converging to one but is slightly higher for most of these markets, and 3) hedging effectiveness is also increasing in hedging horizon. The best hedging decision for these markets is to hedge long-term at about 6 to 8 weeks with a slightly greater than one hedge ratio. These findings provide insights and a better understanding of the characteristics and properties that shape the effectiveness of futures commodity trading, insights that are valuable and relevant to the general commodity hedger.

In 2003, a survey taken as part of the Corporate Executive Board Procurement Strategy Council (2003) revealed that 41% of risk managers believe that their procurement department will become significantly more important in the coming years and, critically, over 50% acknowledge that the effectiveness of their procurement organization's risk management division needs significant improvement. In fact, these managers ranked commodity price risk as more relevant than currency price risk by a 3 to 2 ratio. Consequently, it is no surprise that hedging demand in the metals markets is such that, over the period from Jan-June 2005 to Jan-June 2006, non-precious metals futures trading increased by 21% in volume and the volume for aluminum contracts alone increased by 32% (Holz (2006)). Wall Street is responding to the demand by hiring more traders and new product developers. Barclays aims to hire 20% more staff in 2007 after it already increased staff by 35% the previous year (Freed (2007)). Market demand projections see no end to this trend. In the aluminum market, demand is projected to grow by 9.4% in 2007, following on the 2006 8% growth. This matches unfavorably with the projections in supply. The International Primary Aluminum Institute forecasts an increase in production in 2007 of 6.5% and an increase in 2008 of 3.4%. While metals producers can expect profitable years, metal consumers are faced with difficult choices and reduced profitability. Market conditions point to the need for a concerted risk management policy at the corporate level.

The hedging literature is vast and covers both the motives for hedging and the strategies used to address these motives. For the current study, it is important to recall two areas of the literature. First, one branch of the literature aims to justify the use of hedging by procurement divisions (Froot et al (1993), Hansen and Nohria (2004), Koppenhaver and Swidler (1996)), while the second helps determine how best to select optimal futures positions that minimize the risk inherent in the spot (cash) market (chronologically, Fletcher and Ward (1971), Benninga et al (1984), Perron (1989), Baillie and Meyers (1990), Chowdhury (1991), Lien and Luo (1993), Geppert (1995), Alexander (1999), Chen, Lee and Shrestha (2004)). This study is an investigation into the ***optimal hedge ratio*** and ***hedging effectiveness*** for base metals.

Hedging in futures markets involves taking a futures position opposite to that of a spot market position (Institute for Financial Markets (1998)). For commodity purchasing departments, the futures markets effectively represent a pricing mechanism in the commodity purchasing process. One common definition of the optimal hedge ratio is "…the ratio of the covariance between spot and futures prices to the variance of the futures price" (Myers and Thompson (1989)). Intuitively, the optimal hedge ratio defines the futures market position that will simultaneously minimize the risk absorbed in the spot market or, plainly, what amount of the commodity should be hedged with futures. We also look specifically at the hedging horizon, as previously studied by Chen, Lee, and Shrestha (CLS) (2004) using cointegration to estimate the optimal hedge ratio, to determine whether hedging effectiveness improves across greater hedging time horizons.

This study analyzes the six base metals traded on the London Metal Exchange (LME): aluminum, copper, lead, nickel, tin, and zinc. The use of LME base metals is beneficial given its global acceptance as the world's leader in metal futures trading. It is also interesting to study these futures and their respective hedging effectiveness given their dramatic upswing in volatility over the past few years: the six base metals volatilities increased by 174% on average.

The paper first presents a review of the academic literature then Section III presents the empirical questions. In Section IV, we present the data and the methodology. Section V reports the results and we conclude in Section VI.

II. LITERATUTE REVIEW

Our study builds on the last 25 years of the optimal hedge ratio literature. Our empirical models for estimation are based on the body of research that started with Ederington in 1979. This research area evolved through three phases. First and notably, Ederington (1979) established the first empirical models; later more sophisticated techniques of GARCH estimation were applied, and most recently approaches of cointegration have been used.

Ederington (1979) is the first to empirically estimate optimal hedge ratios and is accordingly credited with formulating the theoretical framework. Ederington summarizes the three working theories of hedging at the time: 1) Traditional Theory, 2) Theories of Holbrook Working, and 3) the Portfolio Theory. He finds fault with Traditional Theory, the leading theory at the time. Ederington challenges its convenient yet unrealistic assumption that a change in futures price is exactly proportionate to a change in cash prices. Ederington argues that the theories of Holbrook Working improve on the inherent weakness of the Traditional Theory by bringing light to the fact that most hedgers do account for the dynamic information the cash-futures basis provides at the time the hedge is placed. Still, the study argues that a more realistic approach is to view hedging in a risk and return framework best formulated by an approach that combines Portfolio Theory and Working's Theory. This provides rationale as to why a hedger may at different times be either hedged or completely un-hedged.

Ederington's seminal contribution to the optimal hedge ratio literature is the empirical finding that even pure risk minimizers will hedge less than their spot market requirements which is contrary to the findings of preceding research. Moreover, he finds that hedging effectiveness improves across two time horizons for financial security futures. Specifically, his findings show that the futures markets for two financial securities prove to be more effective hedging instruments over longer periods. However, the limitation of only using two time horizons, along with the arbitrary method of defining a long period as four weeks and a short period as one week, jeopardizes the applicability of Ederington's conclusions. Furthermore, the study assumes that the minimum variance hedge ratio is simultaneously the optimal hedge ratio without formally proving or interpreting this relationship. A second related weakness lies in the assumption that a hedger who maximizes profit will simultaneously be minimizing the variance of the hedge.

In consideration of these limitations, several important studies quickly addressed these concerns. Benninga, Eldor, and Zilcha (1984) respond first, finding fault in the latter of the two weaknesses. Benninga et al. (1984) find that assuming a hedger has a quadratic utility function presents 'undesirable properties' for estimation and also point out that the assumption that the minimization of producer income variance is equivalent to the optimal hedge ratio is theoretically inappropriate. Instead, Benninga et al. do prove that, in unbiased futures markets, the minimization of income variance is equivalent to the optimal hedge ratio.

Benninga et al. make two assumptions: 1) the futures price is an unbiased predictor of the future spot price, $[\mathbf{F_0=E_0(F_1)=E_0(P_2)}]$, and 2) the regressibility of spot prices on futures price, $[\mathbf{P_1= \alpha + \beta F_1 + \varepsilon}]$ where ε is homoscedastic. $\mathbf{F_0}$ represents the futures price at t=0, $\mathbf{F_1}$ represents the futures price at t=1, and $\mathbf{P_2}$ represents the spot price at t=2. Therefore, both $\mathbf{F_1}$ and $\mathbf{P_2}$ are unknown prices that the producer faces in everyday hedging decisions. In unbiased markets, the only reason for the producer to hedge is to minimize risk, given that on average there will be little to gain in an unbiased market. Therefore, the optimal hedge is where $\mathbf{X=\beta Q}$ with $\mathbf{Q}$ representing the quantity required in the spot market and $\mathbf{X}$ representing the optimal amount hedged on the futures market. Assumption 2 may be econometrically troublesome since the use of price levels can lead to autocorrelation with the residuals. Therefore, using price changes, $[\mathbf{(P_1 - P_0) = \alpha + \beta(F_1 - F_0) + \varepsilon}]$ rids the model of autocorrelation. This model still yields the optimal hedge ratio under the assumption of unbiased futures markets. The only uncertainty remaining in the producer's expected income is the residual and the regression coefficient, $\boldsymbol{\beta}$, is the minimum variance hedge ratio. The strength of their results "…derives from its generality (it is free from assumptions about utility functions) and from the ease of its applicability (it requires only a regression analysis to derive the optimal hedge ratio)" (Benninga et al (1984)).

Following the research by Benninga et al (1984), the empirical estimation of the optimal hedge ratio was improved by accounting for cointegration between spot and futures prices. One of the key findings is that spot and futures prices tend to drift together over time. Chowdhury (1991) proves that "…the market efficiency hypothesis requires that the current futures price and the future spot price of a commodity are close together." This follows from the definition of market efficiency which implies that current prices should reflect all current and past price information in establishing current market prices. Chowdhury uses price data from the LME to test the hypothesis of market efficiency (cointegration) for copper, lead, tin, and zinc.[1] Cointegration is found between the four base metals studied suggesting that the use of conventional estimation techniques to estimate the optimal hedge ratio would lead to over-hedging. A model that fails to incorporate the long run co-movement between variables does not capture the mean reverting tendency of the model, which leads to an upward bias in the point estimates in the model.

[1] Base metals are some of the most commonly traded futures contracts, yet this is the only study to incorporate base metals in the optimal hedge ratio analysis. It should be noted that the Chowdhury study does not give any attention to hedging strategy, paying all of its attention to the statistical properties of cointegration.

Lien and Luo (1993) address the problem of over-hedging by estimating the optimal hedge ratio using an error correction model to account for the issue of cointegration the Chowdhury study raises. Lien and Luo run their estimation at 9 hedging horizons and find that the optimal hedge ratio tends to fluctuate before converging towards one suggesting that the optimal hedge ratio converges to the naïve hedge ratio over time. These findings were later augmented by Geppert (1995), who establishes that hedging effectiveness and the optimal hedge ratio both depend on the permanent and transitory components of the price changes between spot and futures prices. "Over long horizons, the shared component ties the spot and futures series together and the two prices will be perfectly correlated" (Geppert (1995)). A major weakness in the Geppert study is the model requirement that both spot and futures prices be I(1) to implement the Stock and Watson (1988) methodology suggested in the study. It would be useful to adopt a methodology that provides valid hedge ratios when the unit-root condition is not satisfied.

Such a study is Chen, Lee and Shrestha (CLS) (2004). CLS empirically estimate the optimal hedge ratio with a cointegration methodology that does not require both the spot and futures prices to contain a single unit root. They are able to estimate both the short-run and long-run hedge ratios with the Pesaran et al (2001) approach that does not require both series to be I(1) or I(2) together. This approach works when prices are unit root processes and when they are stationary. In all, 9 different hedging horizons are considered over 25 different commodities. As expected, they find that the futures and spot prices share a stochastic trend implied theoretically by market efficiency and the no-arbitrage condition. In estimating the optimal hedge ratios they find that hedging effectiveness does improve over greater hedging horizons and that the short-run hedge ratio is significantly less than one. Our study of the six LME metals follows the CLS methodology.

III. EMPIRICAL QUESTIONS

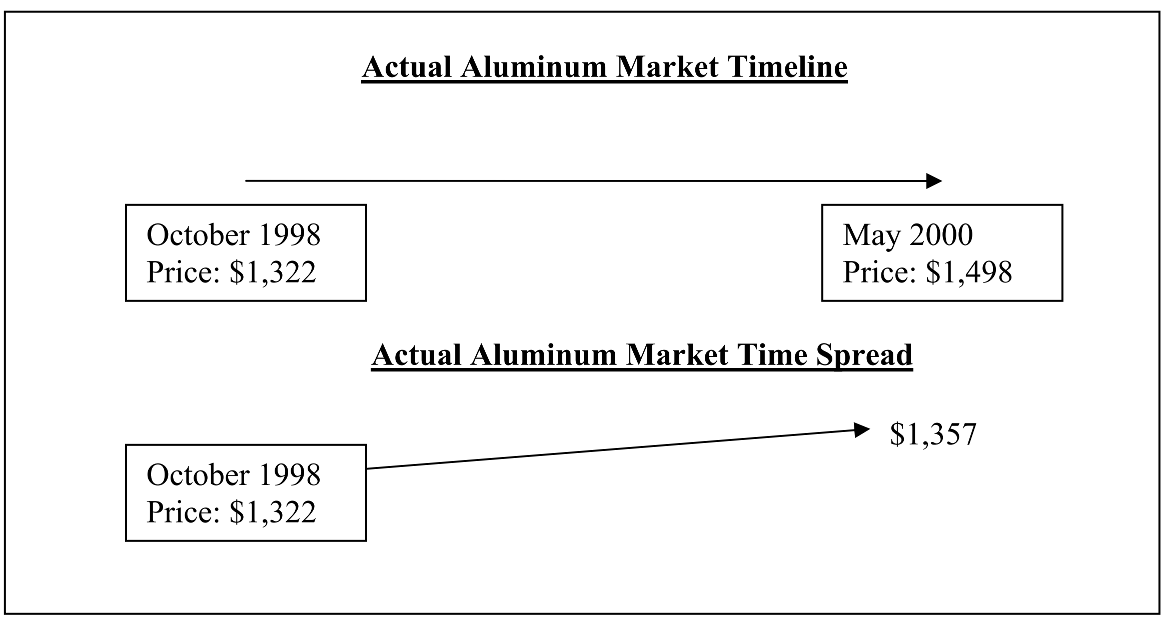
In principle, futures markets exist to offer buyers and sellers of the underlying commodities, financial instruments, or index the opportunity to minimize the price risk inherent in cash market positions. These open markets allow for better price discovery. Moreover, futures markets are appealing to firms because of high liquidity and ease of entry/exit properties. Various businesses across the globe utilize these advantageous properties to manage price risk exposure. This translates to firm cost savings as they mitigate their risk exposure. Firms especially adept at risk management will likely survive periods of high price risk and volatility. Given the recent competitive nature of the commodity landscape, firms are implementing and plan to implement multitudes of hedging strategies to trim the costs of elevated commodity prices.

In commodity purchases, hedging using futures contracts can be thought of as offsetting the risk imposed by a firm's commodity requirements. A firm that requires a fixed amount of copper in the production of their good would want to offset their market price risk by buying copper futures against their annual requirements. Under a futures contract, the price is set for delivery at a future date. Therefore, if the trader is anticipating a bullish copper market, she would be wise to assume a long position defined as buying deferred month futures contracts. This allows the trader to realize this gain in futures prices which would alleviate the upside price risk in the spot market.

Hedging price risk involves not only when to be short and when to be long but it also requires a thorough understanding of the long-run relationship between the spot and futures markets. This may be the most important element in an efficient commodity purchasing department because it ultimately reveals how effective a department is at using the price discovery relationship in formulating hedging strategies. The price discovery relationship implies that spot and futures share a long-run stochastic trend; thus, an effective hedging department would understand that over longer hedging horizons prices tend to revert to the mean together. For these reasons, the hedging horizon is the key issue being addressed in this research. Given the volatile and upward trending data employed in this study, it seems appropriate to hypothesize that the hedging effectiveness of a firm with a comparatively longer hedging horizon would be much more effective in minimizing risk over our data period. The current research consensus is that spot and futures markets move together over long horizons. This implies that a firm facing adverse upside price risk would be wise in lengthening their hedging horizon to offset the unfavorable prospect of increasing spot market prices.

Let us look at a trading scenario in the aluminum futures market to emphasize the importance of effective risk management. Consider major American beverage industry players such as Pepsi-Cola Co., Anheuser-Busch Inc., Miller Brewing Co., and Coca-Cola Co. All of these firms have significant annual aluminum requirements. Correspondingly, all these companies assume a long position in the futures markets because they are always in demand of (buying) aluminum to package their respective products. Aluminum has recently experienced a 41% increase in its mean historical futures price. Likewise, the spot market prices followed this trend but in an often erratic and unpredictable fashion. This naturally introduced a considerable amount of basis risk, making the hedging decisions by commodity traders within these companies difficult at best. Basis risk is the unexpected fluctuations in the prices of cash and futures that is a product of influences ranging from seasonality to supply disruptions. All of these firms likely would have endured this period unsuccessfully without the use of some form of hedging strategy.

Consider a beverage company, similar to one of the firms mentioned above, with an annual and realistic aluminum requirement of 100,000 metric tons (MT). The standard aluminum contract is specified for 25 MT at some point in time for future delivery. Now, consider the price of $1,322 for cash aluminum in October of 1998 and compare it to the prices prevailing in May of 2000.



The market in October was in contango as indicated by the futures price being greater than that of the market. Therefore, pursuing the recommended strategy above would lead to hedging the spot market position of 100,000 MT. This strategy would lock in the price of $1,357/MT on October of 1998 for delivery in May 2000. Assuming away transaction costs, this simple hedging strategy would save the hypothetical firm $14M dollars (= (1,498-1,357) * 100,000). The questions a commodity hedger has to answer before implementing her strategies include: what is the best hedge ratio and what is the best time horizon for this hedge? Our methodology allows us to answer these two questions.

IV. ECONOMETRIC METHODOLOGY

Table 1 shows the six metals markets our data set covers. All these metals are traded on the London Metal Exchange: Aluminum, Copper, Lead, Nickel, Tin, and Zinc. Our dataset is longer than those in previous studies and provides the daily close price for both the cash and futures prices dating back to July of 1998 and up to October 2006. The futures data is collected from Futuresource, a database specifically designed for commodity traders. The futures price data represent the near-by futures contract or the contract with the closest settlement date and rolled over 10 days prior to expiration. Cash prices used are very closely related to the second bell close on the LME, since nearly all metals pricing is based on this quote.

[INSERT TABLE 1 HERE]

Table 2 illustrates the recent increased volatility in the metal markets: the price standard deviation increased across the six metals by an average of 174%. The table also reports the ratio of the standard deviation to the mean price to indicate how volatility increased in proportion to the average price for all six of the base metals. This statistic indicates that both mean prices and standard deviation increased over the period. Figure 1 illustrates the increased volatility prevailing in the current commodity landscape. The figure shows the dramatic upward shift in prices that has occurred in all six of the contacts over the last two years of our sample. We observe that mean aluminum futures prices increase over 41% after the break point in March 2005, with a record high being reached on May 11, 2006. Copper provides a similar story, but the mean futures prices more than doubles (137%) with a record high also being reached on May 11. The copper contract is usually regarded as the leading base metal, primarily because of its large trading volume, which helps explain the contract's significant uptrend in comparison to aluminum, lead, nickel, and tin. Finally, Panel A illustrates the increase of futures prices in the zinc market of over 100%. Lead's historical prices reached a record high on October 16 and the mean futures price increasing over 77%. Nickel's price path parallels that of copper with its price more than doubling (124%). Again, the record high was established on October 16. Tin increases modestly in comparison to Lead and Nickel with a much less dramatic increase of 51% with a record high being set on October 16.

[INSERT FIGURE 1 HERE]

[INSERT TABLE 2 HERE]

Empirically, the estimation follows the derivation provided by Benninga et al. (1984). First, let's assume that a commodity purchasing department for a beverage company has to buy some quantity (Q) of aluminum at t=1. The price (P_1) at period t=1 is uncertain since one is unable to predict future prices. The commodity trader can purchase futures (F_0) at t=0 to offset the uncertainty of the price (P_1) at t=1. The income of the firm after implementing the hedge is, therefore, represented in equation (1) below,

$$QP_1 + X(F_0 - F_1) \quad (1)$$

where F_1 represents the futures price at t=1 and X represents the trader's hedge. In this case, the quantity X represents a long position in the futures market and the difference in the two futures prices will establish whether the hedge was favorable.

In order to derive the optimal hedge ratio, one must assume that the futures market is an unbiased predictor (market efficiency) of the spot market which is denoted below in equation (2). This assumption is not unrealistic given the wide body of research on cointegration that indicates that futures and spot prices do share a mean-reverting relationship in the long run (Lien and Luo (1993), Geppert (1995), Alexander (1999), CLS (2004)). It is also assumed that the spot price shares a linear relationship with the futures market or that spot prices can be regressed on futures prices. This holds if ε, the error term, is not correlated with F_1 (Benninga et al (1984)).

$$F_0=E_0(F_1)=E_0(P_2) \quad (2)$$

$$P_1 = \alpha + \beta F_1 + \varepsilon \quad (3)$$

Subsequently, the variables are differenced to rid the model of this inherent problem as illustrated below in equation (4). All the assumptions still hold if equation (4) is estimated in favor of equation (3).

$$(P_1 – P_0) = \alpha + \beta\ (F_1 – F_0) + \varepsilon\ (4)$$

Equation (5) replicates equation (1) but in this case the dependent variable is included to capture the income of the firm after the hedge is completed.

$$I = QP_1 + X^*(F_0 – F_1)\ (5)$$

The expected income of the firm is found to equal the cost of the spot market requirement under the unbiasedness assumption in equation (2). This relationship is denoted below in equation (6), where the two futures prices cancel out under the assumption of unbiasedness. The only reason remaining to hedge is to minimize the risk that the commodity poses.

$$E_0(I) = Q^*E_0(P_1) + X^*(F_0 – E_0(F_1)) = Q^*E_0(P_1)\ (6)$$

If the commodity trader allows his hedge position to equal the product of the coefficient in the regression equation (β) with the physical requirement of the commodity (Q) then equation (7) below follows. This is the result of substituting (β * Q) for X in equation (5).

$$I = Q\ (P_1 - \beta\ F_1) + Q\ \beta\ F_0\ (7)$$

Solving equation (3) for (P_1 - β F_1) allows the substitution of (α + ε) into equation (8) below:

$$I = Q\ (\alpha + \varepsilon) + Q\ \beta\ F_0\ (8)$$

Equation (8) proves that the optimal hedge ratio is X = (Q β) and it indicates that the only remaining uncertainty in the equation is in the error term which, by definition, cannot be hedged. Therefore, all income variance is eliminated and the only reason for the trader to hedge is to minimize the risk variance captured by (Q β). This finding proves that the minimum variance hedge ratio is also the optimal hedge ratio.

Equation (9) represents the minimum variance hedge ratio defined by Ederington (1979) when the trader/producer is attempting to minimize income variance.

$$\text{Var } I = Q^2 \text{ Var } P_1 + X^2 \text{ Var } F_1 - 2\,Q\,X \text{ Cov } (P_1 , F_1) \quad (9)$$

The minimum variance hedge can also be represented as equation (10) below with the use of simple differentiation:

$$X = Q \text{ Cov } (P_1 , F_1) \,/\, \text{Var } F_1 \quad (10)$$

Note that X/Q is equivalent to β, the coefficient representing the hedge ratio in equation (4), which is also equivalent to the expression Cov (P_1 , F_1) / Var F_1.

Given this proof, it is theoretically valid to empirically estimate the optimal hedge ratio with the differenced form equation (4) above. Before estimating this model, it needs to be addressed how the optimal hedge ratio will be estimated for the different hedging horizons. These estimation techniques are produced in the studies by Geppert (1995) and CLS (2004). Both studies prove that the price changes (ΔP_t and ΔF_t) in equation (4) should be k-period differenced to properly estimate a respective k-period hedging horizon optimal hedge ratio. Simply put, this means that the frequency of the data must match the hedging horizon of the estimated optimal hedge ratio. A major drawback in the Geppert study is the use of overlapping differencing to prevent the sample size from becoming too small. As CLS points out, such a method produces correlated observations which lead to a regression that has autocorrelated error terms. This should be avoided to eliminate the upward bias in estimates of the statistical significance of coefficient estimates. The sample size in the present study is large enough to warrant the use of non-overlapping differences which prevents the troublesome properties of autocorrelated error terms produced by overlapping differencing.

The next step in the methodology is to test for unit root in the prices for both the spot and futures in all six of the base metals. This is necessary because, as market efficiency implies, futures and spot prices should move together over time. Under market efficiency, if the futures move in one direction then so do the spot prices, implying that if both series are I(1) then they also should be cointegrated. Perron (1989) unit root tests are performed to account for the breaks in the data that are quite obvious when visually examining Figures 1-6. This method tests for stationarity after detrending the series and allowing for structural breaks. The structural breaks in this test should be exogenous. This is easily supported in the base metals as speculative hedge funds have increasingly emerged in commodity markets to create more balanced portfolios. This phenomenon has coincided with the price increases outlined in Figures 1-6 and would be difficult to conceive as anything but exogenous in the causality of futures prices. Detrending the series using both slope and intercept shifts are employed after several updates to the study have shown this method to be preferred (Pesaran (1997)). Choosing the break points for these tests is done by visually examining the data to determine the break in the data which is used in estimating the test statistic.

After the unit root tests are performed, it is necessary to evaluate whether cointegration exists among the prices of both the futures and spot markets. Again, market efficiency implies that this is the case. CLS only assumes cointegration so this study improves upon this by empirically verifying the long-run co-movement. Cointegration is tested using the Pesaran et al method (2001) which transforms equation (4) into the unconstrained version of the error-correction model denoted by equation (11) below:

$$\Delta P_t = \alpha - \beta_1 \Delta F_{t-1} - \beta_2 \Delta F_{t-2} + \beta_3 \Delta P_{t-1} + \beta_4 \Delta P_{t-2} + \Phi_1 F_{t-1} + \Phi_2 P_{t-1} + \varepsilon_t \quad (11)$$

In (11), two lags are included for the purpose of uniformity but in the actual estimation of the test, lags will be determined with the Akaike Information Criterion (AIC) model selection test. The Pesaran approach uses an F-statistic to test whether the lagged level variables are jointly significant [$\Phi_1 = \Phi_2 = 0$]. Critical values for these tests are obtained from the study by Pesaran et al (2001). These tests are performed with the weekly data that are also used in the unit root tests.

After testing for cointegration, the simultaneous equation models considered by Pesaran (1997) in equation (8) of that study is adapted to jointly estimate the ratios, which allow us to evaluate the long-run relationship that exists between spot and futures prices enabling a dynamic model that corrects short-run deviations from the long-run equilibrium (Alexander (1999). Equation (12) is "…parameterized so as to be closely associated with the error-correction models encountered in the vector autoregressive models with cointegration" CLS (2004):

$$(P_1 - P_0) = \alpha_1 + \alpha_2 P_{t-1} + \alpha_3 F_{t-1} + \beta (F_1 - F_0) + \varepsilon \quad (12)$$

This equation differs from the error correction model in that ΔF_t is used instead of the ΔF_{t-1} term that the vector autoregressive model yields. This alteration is supported theoretically in the CLS study which uses ΔF_t because it explicitly represents the short-run hedge ratio. Additionally, a simultaneous equations approach is avoided because the interest lies **only** in the short-run and long-run ratios. In equation (12) both the short-run and long-run hedge ratios can be estimated where $-\alpha_3 / \alpha_2$ is the long-run hedge ratio, as proved by Geppert, and β is the short-run hedge ratio. This eliminates the problem associated with equation (4) only incorporating short-run information. It is anticipated that the long-run hedge ratio will remain constant and that the short-run ratio will converge to the long-run ratio across greater time horizons. Equation (12) is supported theoretically by CLS and adapted from Pesaran et al.

The final and most important step in the methodology involves testing the out-of-sample hedging effectiveness. Out-of-sample hedging effectiveness will enable the researcher to evaluate how effective the hedging strategy is over increasing hedging horizons. Using equation (13) as the hedged portfolio, hedging effectiveness will be determined by equation (14) which frequently serves as a measure of hedging effectiveness in the body of research on optimal hedge estimation (see among others, Anderson and Danthine (1981) or Meyers and Thompson (1989)):

$$\Delta V_h = Q\,(\Delta P_t) + X(\Delta F_t) \quad (13)$$

$$1 - [\mathrm{Var}(\Delta V_h) \,/\, \mathrm{Var}\,(\Delta P_t)] \quad (14)$$

The first half of the sample will be utilized to compute the optimal hedge ratio across all of the hedging horizons with these estimated hedge ratios being substituted for

X in equation (13). Furthermore, the second half of the data set will be used in calculating the remainder of the coefficients with Q being set to 1. Ultimately, this equation represents the amount of variance reduced with the implementation of the hedge above and beyond that of an unhedged position.

V. RESULTS

The first part of the methodology involves testing for unit root or the stationarity of the variables. Table 3 shows the results of the unit root tests conducted on the weekly data for each market. All the variables except for the futures prices on zinc appear to be I(1) or integrated of order 1. The λ represents the proportion of the sample at which the break point occurs, measured from the beginning of the data sample to the breaks, which are determined visually.[2] The finding on zinc might be attributed to the low power of unit root tests. In any case, the test statistic is close to passing the test and would hypothetically pass at the 12% level of significance. The DF-GLS test was also used to provide further insight into the results, and the finding from this test shows that zinc does in fact have unit root. These findings coupled together point to zinc futures being I(1). The fact that the cash prices have unit root suggests the futures should as well, given the no-arbitrage condition and market efficiency condition assumed in the literature (CLS (2004)). Therefore, all prices are assumed to suffer from unit root.

[INSERT TABLE 3 HERE]

[2] A range of possible break points were selected including the minimum, mean, and maximum. All three of these were tested with their respective lambda statistic and all proved to change the results very little. Also, the test statistics were calibrated as needed to more appropriately capture a break that falls between the values offered in the study. These were altered approximately 0.75 for each incremental move away from the lambda statistic to produce more reliable estimates.

Given that all the variables appear to be integrated of order 1, the optimal hedge ratios are calculated for 9 hedging horizons ranging from one day, one week to eight weeks. The results are reported in Table 4. All the estimates in Table 4 prove to be significant at the 1% level of significance. Estimation of the ratios is performed using simple OLS from equation (4). The variables are differenced to account for unit root and autocorrelation. Ultimately, all the optimal hedge ratios do not converge towards one across greater hedging horizons. Many of them do appear to fluctuate across the horizons but each of the markets exhibit a distinct trend (except aluminum) towards a value greater than one. The very short horizon (one-day) optimal hedge ratios are all less than 0.65 but, as soon as the differentiation frequency is increased to 1-week, the optimal ratio increase to a range from 0.83 (Tin) to 0.99 (Nickel). The ratio at the 4-week horizon are all greater than 1, ranging from 1.00 (Aluminum and Copper) to 1.11 (Nickel). At the longest time horizon we study, the optimal ratios range from 1.00 (Aluminum) to 1.17 (Nickel). Overall, the average (median) 8-week hedging horizon across the six metals is roughly 1.074 (1.066). Empirically, this means that the trader should be hedged 7.4% above the respective spot position. This finding is contrary to the findings of CLS and Geppert who both found that the optimal hedge ratio converges to one across greater time horizons. Table 4 suggests that, in general, the proportion of spot positions to be covered by opposite positions on futures markets is greater than one. This finding is of importance, but at this point, should be considered preliminary since the I(1) prices in this study are assumed to trend together over time which can lead to misleading results in an OLS regression (Chowdhury (1991)).

[INSERT TABLE 4 HERE]

Given that all the variables in the model contain unit root, it is anticipated that all the relationships between spot and futures prices share a long-run stochastic trend. Table 5 verifies that each of the 6 markets studied do share a mean-reverting relationship, as in each case the test statistic is greater than the upper I(1) bound found in the Pesaran study. The test employed here has two variables (k), an intercept, and no trend. The 10% critical value is 4.14 in this case, which means that for the series to be cointegrated the test statistic must be greater than the 4.14 test statistic. The use of this test improves on several earlier studies that used the Engle-Granger method. Using this test takes advantage of the minimum variance criterion used in the test that is also used in the risk management application of this study (Alexander (1999)). These tests were reinforced with the Engle-Granger test that provided the same conclusions as the Pesaran approach.

[INSERT TABLE 5 HERE]

Having confirmed that all the variables within each respective market are cointegrated, the associated joint estimation that ties this long-run co-movement together is performed. The estimation approach is CLS's which jointly estimates the long-run and short-run hedge ratios. Table 6 presents the result from this approach and it is apparent that the results are very similar to that of the previous short-run estimation. This estimation, which correctly includes the long-run properties of the cash-futures relationship, should account for the concerns associated with the estimation of equation (4). Correcting for cointegration issues, the results in Table 6 tend to bear out that the naïve estimation of equation (4) leads to over-estimation of the optimal hedge ratio. At the 8-week horizon, the optimal hedge ratio in Table 6 is lower than that in Table 4 for 4 of the 6 metal markets, namely aluminum, lead, nickel and zinc. Nonetheless, the results in Table 6 confirm that, after controlling for cointegration issues, the hedgers should have been overhedged to minimize the variance of their cash position. Namely, market participants should, across the six metals on average, overhedge by 6.7% at the 8-week hedging horizon. One may question whether 7.4% and 6.7% are really different from one another. However, using the hypothetical aluminum requirement of 100,000 MT used in Section III as a benchmark, the two different hedge ratios account for a $1.9M difference when employing the two hedge ratio values. Any firm would be more than glad to add this additional cost avoidance to their portfolio. Again, these findings are indicative of the volatile commodity landscape that has taken form over the recent years.

[INSERT TABLE 6 HERE]

The study by CLS points out that the short-run hedge ratio should approach the long-run hedge in this joint estimation. Table 6 provides confirmation of this fact. First, as one can anticipate, at the one day horizon, the two estimates are very different. The average value of the percentage difference between the two estimates, measured as (Short-run ratio – Long-run ratio) / Long-run ratio, is a high -41%. At the one-week horizon, the difference is already greatly reduced to -7.6% and is further reduced at the 2-

week horizon to -2.7%. Aggregating all other horizons reported in Table 6, the difference narrows to an average 0.1% confirming the convergence but we should note that the sign of this difference is not consistent either across horizon or across markets.

Finally, Table 7 presents the findings of how effective these optimal hedge ratios would be in a portfolio consisting of cash and futures positions. All the metals are considered in this example to thoroughly evaluate the effectiveness of the hedges. All the values appear to exhibit a common trend towards the mid-90% across the hedging horizons. The hedging effectiveness value represents the percentage reduction in variance over and beyond a portfolio unhedged. It is evident that these optimal hedge ratios are useful in minimizing variance but even more important, the hedges improve across the time horizons. Namely, a hedge may be more favorable as the hedging horizon is lengthened given the nature of price discovery in the spot and futures relationship.

[INSERT TABLE 7 HERE]

A viable question in commodity purchasing departments is: how far out a company should hedge given the nature of the commodity landscape? The empirical evidence contained in this study indicates that, in general, a longer hedging horizon may help mitigate the risk in the spot market. The results provided in Table 7 indicate that the optimal hedging horizon should be at 8-week or the longest hedging horizon considered in this study. This statement is not saying that the 8 week effectiveness value is always greatest at this horizon, as in the case of aluminum the 6-week horizon is preferred to the 8-week horizon. Rather, it is evident that these values are generally asymptotically improving across the horizons and therefore, it is inferred that this would also occur across a broader dataset. A longer hedging horizon is the course of strategy advocated in this study.

VI. CONCLUSIONS

This study investigates the optimal hedge ratio and hedging effectiveness for six base metals markets. After applying careful econometrics methods, we first document that the short-run optimal hedging ratio is increasing in hedging horizon. If a corporate hedger is attenuating demand risks for his company with a longer time-frame in the futures market, he should increase his exposure to the futures market as his hedging horizon lengthens. Second, we show that the optimal hedging ratio, contrary to results in other markets, does not converge to the naïve ratio of 1 for our markets over our time-period over longer time horizons. We document that the appropriate position a hedger should take is to over-hedge by over 5% in order to best minimize price impacts. Finally, we find that hedging effectiveness for the optimal hedging ratios we computed in an out-of-sample methodology is very high in the mid-90's in percentage terms. In other words, implementing a hedge with the hedge ratios we determined would eliminate over 90% of price uncertainty for large corporation procurement departments. Overall, the best hedging decision for these markets is to hedge long-term at about 6 to 8 weeks with a slightly greater than one hedge ratio. These results are robust to the increased volatility over our data period and are of great interest to many purchasing departments and other commodity hedgers.

BIBLIOGRAPHY

Alexander, C. (1999), "Optimal Hedging Using Cointegration", *Philosophical Transactions: Mathematical, Physical and Engineering Sciences*, Vol. 357, No. 1758, 2039-2058.

Anderson, Ronald and Jean-Pierre Danthine (1981), "Cross Hedging", *The Journal of Political Economy*, Vol. 89, No. 6, 1182-1196.

Baillie, Richard and Robert Myers (1990), "Bivariate GARCH Estimation of the Optimal Commodity Futures Hedge", *The Journal of Applied Econometrics*, Vol. 6, 109-124.

Benninga, Simon, Rafael Eldor, and Itzhak Zilcha (1984), "The Optimal Hedge Ratio in Unbiased Futures Markets", *The Journal of Futures Markets*, Vol. 4, No. 2, 155-159.

Chen, Sheng-Syan, Cheng-Few Lee, and Keshab Shrestha (2004), "An Empirical Analysis of the Relationship Between the Hedge Ratio and Hedging Horizon: A Simultaneous Estimation of the Short- and Long-Run Hedge Ratios", *The Journal of Futures Markets,* Vol. 24, No. 4, 359-386.

Chowdhury, Abdur (1991), "Futures Market Efficiency: Evidence from Cointegration Tests", *The Journal of Futures Markets*, Vol. 11, No. 5, 577-589.

Corporate Executive Board (2003), "Managing Procurement Risk: Assessment, Monitoring, and Mitigation", *Procurement Strategy Council Teleconference*.

Dickson, Duane, Jim Manocchi, and Sanjay Agarwal (2006), "Commodity Management: Profiting from Volatility", *Chemical Week*, July 2006.

Ederington, Louis (1979), "The Hedging Performance of the New Futures Markets", *The Journal of Finance*, Vol. 34, No. 1, 157-170.

Fletcher, Lehman and Ronald Ward (1971), "From Hedging to Pure Speculation: A Micro Model of Optimal Futures and Cash Market Positions", *American Journal of Agricultural Economics,* Vol. 53, No. 1, 71-78.

Freed, Dan (2007), "Commodity Desk Still Staffing Up: Fear of Price Declines Can't Dampen Enthusiasm for Asset Class", *The Investment Dealers' Digest*, January 29, 2007, 1.

Froot, Kenneth, David Scharfstein, and Jeremy Stein (1993), "Risk Management: Coordinating Corporate Investment and Financing Policies", *The Journal of Finance*, Vol. 48, No. 5, 1629-1658.

Geppert, John (1995), "A Statistical Model for the Relationship between Futures Contract Hedging Effectiveness and Investment Horizon Length", *The Journal of Futures Markets*, Vol. 15, No. 5, 507-536.

Hansen, Morten and Nitin Nohria (2004), "How to Build Collaborative Advantage", *MIT Sloan Management Review,* Vol. 46, No. 1, 22-30

Holz, Rebecca (2006), "Trading Volume", *Futures Industry*, September – October 2006, 10-14.

Introduction to the Futures and Options Markets (1998), "Institute for Financial Markets", accessed August 29, 2006, http://www.theifm.org/tutorial/contracts.htm

Koppenhaver, Gary and Steven Swidler (1996), "Corporate Hedging and Input Price Risk", *Managerial and Decision Economics,* Vol. 17, No. 1, 83-92.

Lien, Donald and Xiangdong Luo (1993), "Estimating Multiperiod Hedge Ratios in Cointegrated Markets", *The Journal of Futures Markets*, Vol. 13, No. 8, 909-920.

Myers, Robert and Stanley Thompson (1989), "Generalized Optimal Hedge Ratio Estimation", *American Journal of Agricultural Economics*, Vol. 71, No. 4, 858-868.

Perron, Pierre (1989), "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis", *Econometrica,* Vol. 57, No. 6, 1361-1401.

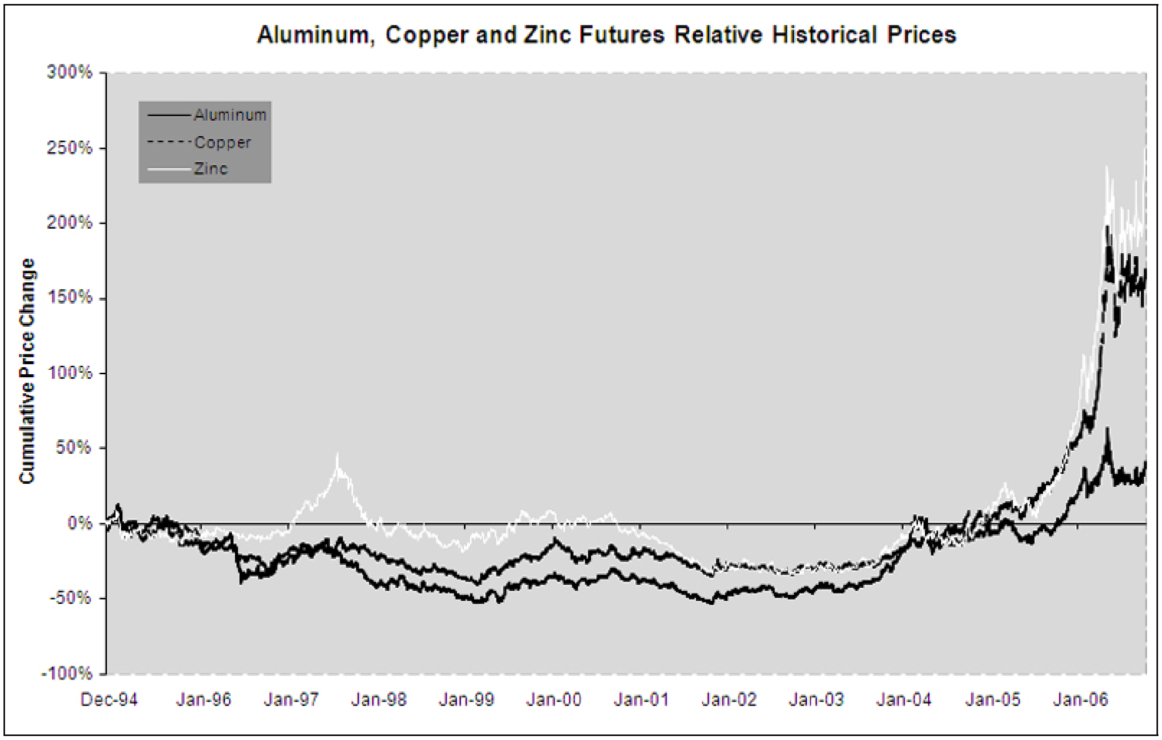
Pesaran, M. Hashem, Youngcheol Shin, and Richard Smith (2001), "Bounds Testing Approaches to the Analysis of Level Relationships", *Journal of Applied Econometrics*, Vol. 16, 289-326.

Pesaran, M. Hashem (1997), "The Role of Economic Theory in Modeling the Long Run", *Economic Journal*, Vol. 107, No. 440, 178-191.

Stock, James and Mark Watson (1988), "Testing for Common Trends", *Journal of the American Statistical Association*, Vol. 83, No. 404, 1097-1107.

FIGURE 1

Figure 1 graphs in two panels the complete time series of data used in the study. In each panel, using the same scale, we highlight the dramatic price increase experienced by the metals markets over the study period. From these representations, we determine break points which are reported in Table 2.



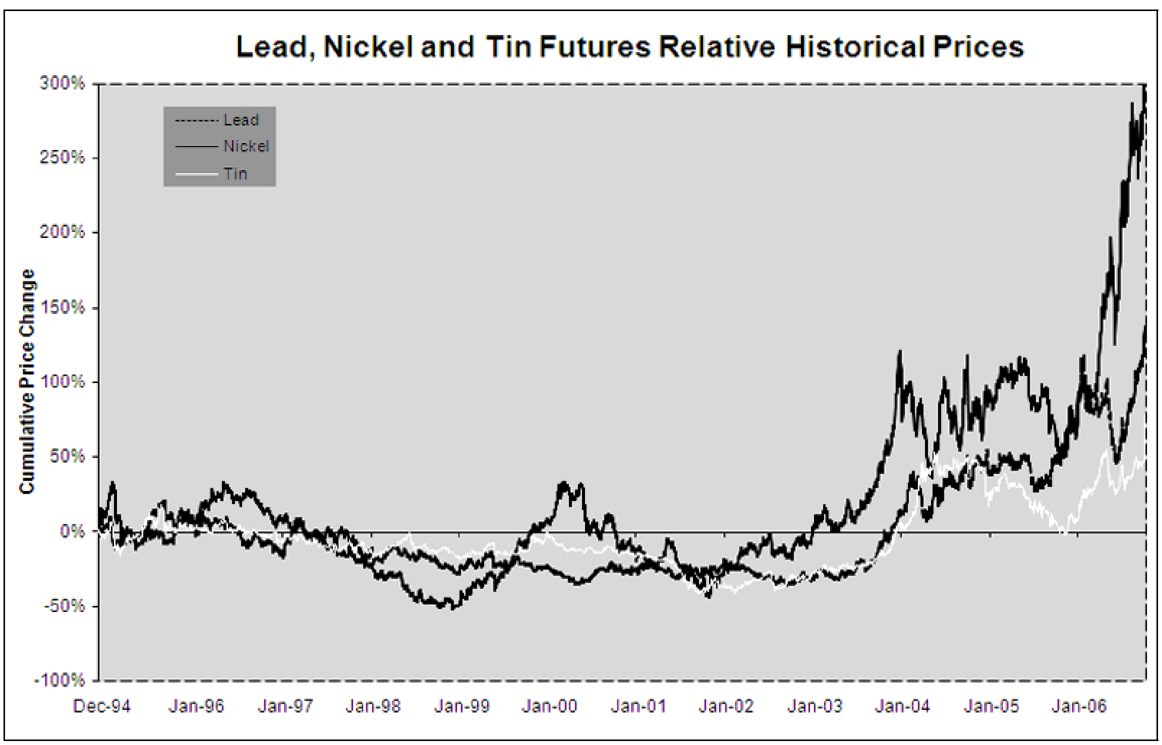


TABLE 1 – Data Description

Table 1 reports the time period and frequency of the data used in our empirical determination of the optimal hedge ratio and optimal hedging horizon. All prices are prices from the London Metal Exchange (LME). The futures price information is obtained from Futuresource, a platform relaying the LME data, and represents the near-by futures contract. The cash prices are related to the second bell close on the LME.

Base Metal	Data Sample Range	Frequency	Observations
Aluminum	*July 8,1998 - October 19,2006*	*Daily*	2068
Copper	*July 8,1998 - October 19,2006*	*Daily*	2066
Lead	*July 8,1998 - October 19,2006*	*Daily*	2068
Nickel	*July 8,1998 - October 19,2006*	*Daily*	2063
Tin	*July 15,1998 - October 19,2006*	*Daily*	2064
Zinc	*July 15,1998 - October 19,2006*	*Daily*	2058

TABLE 2 - Descriptive Statistics

Table 2 reports sample descriptive statistics for the cash prices for all 6 metal markets investigated in the study. Over the sample period, each of these markets exhibited a large change in both price level and volatility level. The table reports the mean, maximum, minimum and the standard deviation of prices for each market for the two distinct periods: before the price level change break and after the price level change break. The break points are determined visually from the historical price charts and are reported in the table below. In addition, the table reports the ratio of volatility to level of prices (σ/μ) before and after the break to confirm that the break represents both a change in level and a change in volatility in prices.

Metal	Before Break	After Break	% Increase
ALUMINUM	**Break Point Date**	**17-Mar-05**	
Mean	**$1,540**	**$2,169**	**41%**
Standard Dev	**$180**	**$354**	**97%**
Maximum	**$2,186**	**$3,180**	**45%**
Minimum	**$1,161**	**$1,688**	**45%**
σ/μ	**0.117**	**0.163**	**40%**
COPPER	**Break Point Date**	**15-Nov-04**	
Mean	**$2,012**	**$4,770**	**137%**
Standard Dev	**$483**	**$1,796**	**272%**
Maximum	**$3,140**	**$8,650**	**175%**
Minimum	**$1,339**	**$2,865**	**114%**
σ/μ	**0.240**	**0.377**	**57%**
LEAD	**Break Point Date**	**29-Jan-04**	
Mean	**$560**	**$989**	**77%**
Standard Dev	**$106**	**$165**	**56%**
Maximum	**$862**	**$1,540**	**79%**
Minimum	**$415**	**$693**	**67%**
σ/μ	**0.189**	**0.167**	**-12%**
NICKEL	**Break Point Date**	**8-Jan-04**	
Mean	**$7,204**	**$16,126**	**124%**
Standard Dev	**$1,777**	**$4,442**	**150%**
Maximum	**$17,100**	**$31,900**	**87%**
Minimum	**$3,785**	**$10,550**	**179%**
σ/μ	**0.247**	**0.275**	**12%**
TIN	**Break Point Date**	**18-Mar-04**	
Mean	**$5,371**	**$8,095**	**51%**
Standard Dev	**$769**	**$887**	**15%**
Maximum	**$7,795**	**$11,000**	**41%**
Minimum	**$3,638**	**$6,000**	**65%**
σ/μ	**0.143**	**0.110**	**-23%**
ZINC	**Break Point Date**	**17-Mar-05**	
Mean	**$1,036**	**$2,213**	**114%**
Standard Dev	**$162**	**$894**	**452%**
Maximum	**$1,672**	**$3,960**	**137%**
Minimum	**$745**	**$1,178**	**58%**
σ/μ	**0.156**	**0.404**	**158%**

TABLE 3 – Perron Unit Root Test

Table 3 reports the results of the Perron Unit Root test performed on both the cash and the futures price time series. The Perron Unit Test allows to determine if the price series is integrated of order 1, I(1). Unit root testing was performed on weekly data. λ represents the proportion of the sample at which the break points occurs. The tests are based on Perron (1989) 10% critical values with both a slope and intercept shift. * denotes an I(1) series or unit root.

Variables		Cash			Futures		
METAL	***Sample Frequency***	**λ**	**Test Statistic**	**Critical Value**	**λ**	**Test Statistic**	**Critical Value**
ALUMINUM	*Weekly (433)*	**0.8**	**-3.34***	**-3.69**	**0.8**	**-3.53***	**-3.69**
COPPER	*Weekly (433)*	**0.7**	**-2.77***	**-3.86**	**0.7**	**-2.51***	**-3.86**
LEAD	*Weekly (433)*	**0.7**	**0.02***	**-3.86**	**0.7**	**0.02***	**-3.86**
NICKEL	*Weekly (433)*	**0.7**	**-0.38***	**-3.86**	**0.7**	**0.14***	**-3.86**
TIN	*Weekly (433)*	**0.7**	**0.71***	**-3.86**	**0.7**	**-0.64***	**-3.86**
ZINC	*Weekly (433)*	**0.9**	**-2.53***	**-3.46**	**0.8**	**-3.97**	**-3.86**

TABLE 4- OLS Minimum Variance Hedge Ratio

Table 4 reports the empirical results of estimating the optimal minimum variance hedge ratio for each of the six metal markets. The estimation in this table relies on Equation (4):

$$(P_1 - P_0) = \alpha + \beta\,(F_1 - F_0) + \varepsilon$$

where the MV Hedge Ratio reported is the point estimate of β in Equation (4) found with an Ordinary Least Squares (OLS) estimation. The table also contains the standard deviation of the estimate and the adjusted R-Square of the OLS regression. The analysis is repeated at different level of differentiation from as short as one day to as long as 8 weeks. Due to data constraint (our time series contains 433 weeks worth of data), we limit our longest hedging horizon to 8 weeks to insure our results remain statistically meaningful.

METAL	Statistic	1 Day	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	6 Weeks	7 Weeks	8 Weeks
ALUMINUM	*MV Hedge Ratio*	**0.475**	**0.909**	**0.973**	**0.996**	**1.002**	**1.020**	**1.067**	**1.054**	**1.006**
	Std. Deviation	(0.020)	(0.020)	(0.028)	(0.028)	(0.031)	(0.036)	(0.031)	(0.038)	(0.029)
	Adj. R-Squared	0.210	0.824	0.853	0.899	0.907	0.903	0.940	0.927	0.959
COPPER	*MV Hedge Ratio*	**0.391**	**0.860**	**1.007**	**1.032**	**1.001**	**1.018**	**1.051**	**0.990**	**1.026**
	Std. Deviation	-0.019	-0.021	-1.027	-0.015	-0.020	-0.025	-0.016	-0.014	-0.016
	Adj. R-Squared	0.178	0.800	0.868	0.973	0.960	0.953	0.983	0.988	0.987
LEAD	*MV Hedge Ratio*	**0.654**	**0.951**	**1.023**	**1.022**	**1.075**	**1.055**	**1.100**	**1.046**	**1.108**
	Std. Deviation	-0.023	-0.027	-0.036	-0.028	-0.049	-0.032	-0.034	-0.034	-0.032
	Adj. R-Squared	0.284	0.749	0.792	0.904	0.820	0.930	0.938	0.941	0.957
NICKEL	*MV Hedge Ratio*	**0.526**	**0.992**	**1.103**	**1.074**	**1.116**	**1.002**	**1.084**	**1.034**	**1.173**
	Std. Deviation	-0.022	-0.025	-0.028	-0.037	-0.032	-0.027	-0.021	-0.047	-0.044
	Adj. R-Squared	0.218	0.788	0.879	0.853	0.920	0.944	0.975	0.892	0.932
TIN	*MV Hedge Ratio*	**0.443**	**0.832**	**0.872**	**1.004**	**1.012**	**1.062**	**1.030**	**1.043**	**1.053**
	Std. Deviation	-0.021	-0.026	-0.028	-0.023	-0.030	-0.043	-0.028	-0.029	-0.032
	Adj. R-Squared	0.185	0.701	0.820	0.903	0.915	0.880	0.951	0.957	0.954
ZINC	*MV Hedge Ratio*	**0.554**	**0.982**	**0.986**	**1.099**	**1.036**	**1.002**	**1.059**	**1.117**	**1.079**
	Std. Deviation	-0.021	-0.020	-0.025	-0.023	-0.024	-0.016	-0.024	-0.017	-0.014
	Adj. R-Squared	0.255	0.853	0.884	0.943	0.948	0.979	0.966	0.986	0.992

TABLE 5 – Pesaran Cointegration Tests

Table 5 reports the results of test statistics about the cointegration of the data series. Specifically, the Pesaran cointegration test (1997) is run. The test employed has two variables (k), an intercept and no trend. The 10% critical value is 4.14 in this case. Cointegration was also found to be the case in Engle-Granger tests using ADF and the Engle-Granger test statistics.

METAL	*# of Lags*	*Beta*	*F-Statistic*	*Cointegration*
ALUMINUM	*5*	*1.02*	*5.06*	*YES*
COPPER	*6*	*0.64*	*7.93*	*YES*
LEAD	*5*	*0.58*	*9.87*	*YES*
NICKEL	*6*	*0.83*	*11.23*	*YES*
TIN	*5*	*0.60*	*6.00*	*YES*
ZINC	*6*	*0.72*	*12.87*	*YES*

TABLE 6 – Joint Estimation of the Short-Run and Long-Run MV Hedge Ratios

Table 6 reports the empirical results of estimating the optimal minimum variance hedge ratio for each of the six metal markets. The estimation in this table relies on Equation (12):

$$(P_1 - P_0) = \alpha_1 + \alpha_2 P_{t-1} + \alpha_3 F_{t-1} + \beta\,(F_1 - F_0) + \varepsilon$$

where the (short-run) MV Hedge Ratio reported is the point estimate of β in Equation (12). The table also contains the standard deviation of the estimate and the adjusted R-Square for that estimation. The long-run MV Hedge ratio is computed as $-\alpha_3/\alpha_2$ and is also reported. The analysis is repeated at different level of differentiation from as short as one day to as long as 8 weeks. Due to data constraint (our time series contains 433 weeks worth of data), we limit our longest hedging horizon to 8 weeks to insure our results remain statistically meaningful.

METAL	*Statistic*	1 Day	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	6 Weeks	7 Weeks	8 Weeks
ALUMINUM	*MV Hedge Ratio*	**0.624**	**0.946**	**0.981**	**0.985**	**0.982**	**1.009**	**1.033**	**1.013**	**0.987**
	Std. Deviation	(0.021)	(0.019)	(0.025)	(0.025)	(0.027)	(0.030)	(0.031)	(0.034)	(0.027)
	-α3/α2	0.990	0.996	0.992	0.997	0.994	0.995	0.991	1.007	0.983
	Adj. R-Squared	0.305	0.859	0.887	0.922	0.935	0.941	0.954	0.954	0.971
COPPER	*MV Hedge Ratio*	**0.487**	**0.901**	**1.022**	**1.036**	**1.009**	**1.044**	**1.063**	**0.999**	**1.042**
	Std. Deviation	(0.020)	(0.020)	(0.025)	(0.015)	(0.020)	(0.023)	(0.017)	(0.014)	(0.016)
	-α3/α2	1.017	1.026	1.033	1.045	1.040	1.046	1.061	1.050	1.060
	Adj. R-Squared	0.227	0.829	0.894	0.976	0.967	0.966	0.987	0.990	0.990
LEAD	*MV Hedge Ratio*	**0.716**	**0.967**	**1.029**	**1.018**	**1.063**	**1.033**	**1.078**	**1.059**	**1.100**
	Std. Deviation	(0.023)	(0.025)	(0.033)	(0.027)	(0.046)	(0.031)	(0.035)	(0.035)	(0.035)
	-α3/α2	1.044	1.053	1.056	1.052	1.064	1.053	1.065	1.065	1.053
	Adj. R-Squared	0.335	0.783	0.830	0.918	0.862	0.944	0.949	0.952	0.963
NICKEL	*MV Hedge Ratio*	**0.597**	**0.996**	**1.088**	**1.055**	**1.109**	**0.999**	**1.059**	**1.051**	**1.128**
	Std. Deviation	(0.023)	(0.024)	(0.027)	(0.035)	(0.032)	(0.028)	(0.023)	(0.047)	(0.048)
	-α3/α2	1.054	1.063	1.068	1.059	1.072	1.033	1.042	1.069	1.091
	Adj. R-Squared	0.262	0.810	0.899	0.889	0.935	0.952	0.979	0.921	0.952
TIN	*MV Hedge Ratio*	**0.596**	**0.908**	**0.926**	**1.004**	**1.009**	**1.066**	**1.015**	**1.043**	**1.033**
	Std. Deviation	(0.021)	(0.024)	(0.026)	(0.024)	(0.030)	(0.034)	(0.025)	(0.024)	(0.028)
	-α3/α2	1.027	1.030	1.030	1.025	1.033	1.038	1.030	1.030	1.024
	Adj. R-Squared	0.285	0.768	0.859	0.927	0.939	0.926	0.965	0.971	0.969
ZINC	*MV Hedge Ratio*	**0.617**	**0.994**	**0.993**	**1.058**	**1.002**	**0.997**	**1.073**	**1.015**	**1.112**
	Std. Deviation	(0.023)	(0.025)	(0.018)	(0.018)	(0.026)	(0.019)	(0.022)	(0.031)	(0.038)
	-α3/α2	1.032	1.012	1.029	1.036	1.032	1.032	1.029	1.031	1.031
	Adj. R-Squared	0.334	0.912	0.947	0.966	0.975	0.977	0.991	0.990	0.991

TABLE 7 – Hedging Effectiveness using Out-of-Sample Analysis

Table 7 reports the empirical results of implementing the optimal long-run MV Hedge Ratio as determined with the technique used in Table 6. However, in order not to resample, we split the sample in two halves. The first half of the data is used to estimate Equation (12) and to determine the optimal long-run MV Hedge Ratio. This optimal Hedge Ratio was then used to put in place a hedged position for the second half of the sample. We keep track of the changes in value of that portfolio defined as Equation (13):

$$\Delta V_h = Q^*(\Delta P_t) + X^*(\Delta F_t)$$

We use the series of ΔV_h to compute the Hedging Effectiveness as defined in Equation (14):

$$1 - [Var(\Delta V_h) / Var(\Delta P_t)]$$

The table contains both the estimated optimal Hedge Ratio and the corresponding Hedge Effectiveness achieved.

METAL	*Statistic*	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	6 Weeks	7 Weeks	8 Weeks
ALUMINUM	*Hedging Effectiveness*	**0.839**	**0.850**	**0.927**	**0.902**	**0.899**	**0.960**	**0.936**	**0.942**
	Optimal Hedge Ratio	**0.923**	**1.037**	**0.976**	**1.080**	**1.052**	**1.090**	**1.026**	**1.1066**
COPPER	*Hedging Effectiveness*	**0.747**	**0.773**	**0.844**	**0.887**	**0.842**	**0.932**	**0.924**	**0.962**
	Optimal Hedge Ratio	**0.876**	**0.912**	**0.995**	**1.015**	**1.091**	**1.074**	**1.084**	**1.031**
LEAD	*Hedging Effectiveness*	**0.916**	**0.935**	**0.921**	**0.943**	**0.957**	**0.949**	**0.965**	**0.966**
	Optimal Hedge Ratio	**0.964**	**1.012**	**1.002**	**1.058**	**1.059**	**1.025**	**1.064**	**1.098**
NICKEL	*Hedging Effectiveness*	**0.789**	**0.815**	**0.860**	**0.892**	**0.926**	**0.935**	**0.947**	**0.953**
	Optimal Hedge Ratio	**0.984**	**1.054**	**1.036**	**1.093**	**1.048**	**1.011**	**1.112**	**1.100**
TIN	*Hedging Effectiveness*	**0.799**	**0.846**	**0.882**	**0.916**	**0.932**	**0.914**	**0.926**	**0.954**
	Optimal Hedge Ratio	**0.914**	**0.938**	**1.012**	**1.009**	**1.045**	**1.037**	**1.055**	**1.041**
ZINC	*Hedging Effectiveness*	**0.869**	**0.881**	**0.900**	**0.912**	**0.897**	**0.925**	**0.946**	**0.979**
	Optimal Hedge Ratio	**0.979**	**0.999**	**1.078**	**1.001**	**1.071**	**1.036**	**1.050**	**1.093**

THE INTRA-INDUSTRY EFFECTS OF LIFE INSURANCE COMPANY DEMUTUALIZATON

Joseph W. Meador[†]
Northeastern University

Emery A. Trahan[1‡]
Northeastern University

ABSTRACT

We examine the impact of demutualization announcements by 13 life insurance companies during 1996-2000 on the value of existing stock-owned life insurance companies and companies in other segments of the insurance industry. Demutualization announcements are associated with negative stock price reactions in the days around the announcement, and with larger and positive stock price reactions in the days following announcement. Overall, the results support the contention that life insurance company demutualizations signal favorable future industry conditions and/or increased likelihood of future acquisitions for all segments of the insurance industry. Active-minded investors may use these results to develop alpha-generating investment strategies.

JEL classifications: G22; L22; L89

Keywords: Demutualization, Stock conversion, Life insurance, Insurance industry

---

[1] We thank participants at the Eastern Finance Association annual meeting, the Academy of Financial Services annual meeting, and an anonymous referee for helpful comments and suggestions. Emery Trahan acknowledges support from the Donald F. Harding Professorship.

[†] Finance Group, 413 Hayden Hall Boston, College of Business Administration, Northeastern University, MA 02115, USA. Tel: (617) 373-4713. Email: j.meador@neu.edu.

[‡] **Correspondence to**: Emery A. Trahan, Finance Group, 413 Hayden Hall Boston, College of Business Administration, Northeastern University, MA 02115, USA. Tel: (617) 373-4568. Email: e.trahan@neu.edu.

I. INTRODUCTION

The life insurance industry and banking industry share a common dichotomy of organizational forms whereby some companies organized as mutually-owned firms, "mutuals," (owned by policyholders or account holders) and others organized as stock-owned firms, (owned by shareholders) coexist in the industry. Competitive pressures, access to capital markets, limited liability, and regulatory changes in the banking industry have led many mutually-owned banks to convert to stock-owned companies. More recently this phenomenon has been exhibited in the insurance industry, with several mutually-owned life insurance companies undergoing conversion into stock-owned companies. This demutualization presents research opportunities to better understand the causes and consequences of the change in organizational form. We examine one dimension of the demutualization of life insurance companies—the intra-industry effects.

Demutualization of a life insurance company may signal future growth for the industry as a whole, leading to increased stock valuations for competitors in the industry—the *information effects* hypothesis. Conversely, demutualization may signal that the firm is moving to a stock-owned form to raise additional capital for growth and better competitive position within the industry, leading to reduced stock valuations for existing competitors in the industry—the *competitive pressure* hypothesis. A better understanding of these effects will provide useful information to investors and managers seeking to evaluate the impact of organizational structure changes on the value of firms in the insurance industry.

We examine two relevant research questions. First, do life insurance company demutualizations impact the value of competing stock-owned life insurance companies? And second, do life insurance company demutualizations impact the value of stock-owned companies in other segments of the insurance industry? With regard to the first research question, we find a statistically significant negative announcement effect around the event date, consistent with the *competitive pressure* hypothesis, and larger positive announcement effects in periods up to 30 days subsequent to the event date, consistent with the *information effects* hypothesis. With regard to the second research question, we also find a statistically significant negative announcement effect around the event date, consistent with the *competitive pressure* hypothesis, and larger positive announcement effects in periods up to 30 days subsequent to the event date, consistent with the *information effects* hypothesis.

Taken together, these results indicate that there is significant information contained in demutualization announcements by life insurance companies. This information affects both stock-owned competitors in the life insurance industry and firms in other segments of the insurance industry in a similar fashion. The results are consistent with both the *competitive pressure* and *information effects* hypotheses. Given the larger and longer-term nature of the positive announcement effects, the results are more supportive of the *information effects* hypothesis. Life insurance company demutualizations signal favorable future industry conditions and/or increased likelihood of future acquisitions for all segments of the insurance industry.

These results also have implications for active investors seeking alpha-generating return strategies around life insurance demutualizations. Given the short-term negative stock-price reaction followed by the longer-term positive response, active investors can generate positive abnormal returns by longing publicly traded firms in the insurance industry following a demutualization announcement by a life insurer.

The remainder of the paper is organized as follows. In Section II we provide a summary of the relevant literature and the objectives of this research. In Section III we describe the sample and research method. Section IV contains the empirical results. In Section V we provide a summary and conclusion.

II. LITERATURE REVIEW AND TESTABLE

The life insurance industry exhibits a dichotomy of organizational forms whereby some companies are organized as mutually-owned firms, owned by policyholders, and other firms are organized as stock-owned companies, owned by shareholders. A recent report by Optima (2000) notes that the life insurance industry is rapidly changing due to increased competition, falling regulatory barriers, globalization, the Internet, demographics, and a shift in product demand. In response to these changes, many insurance companies are moving to demutualize in response to increased competition and a drive to become more efficient. Demutualization and future growth opportunities have also been facilitated by the passage of the Gramm-Leach-Bliley Act in 1999. The phenomenon has recently extended to the Japanese market with an announcement by Mitsui Mutual that it would convert to stock ownership in April 2004; see AFX (2003).

Demutualization brings with it numerous advantages and disadvantages. Advantages include: increased management accountability, discipline from the capital markets, increased access to capital for internal growth and acquisitions, and increased access to the managerial labor market. Disadvantages include: high conversion costs, policyholders may pay more for policies, increased agency costs, and short-term pressures from Wall Street. Smith and Stutzer (1995) note that information asymmetries and agency problems offer possible explanations for the organizational choice of insurance companies. They argue that informational asymmetries do more to explain the kinds of contracts offered by mutuals than do agency problems. Spiller (1972), Spiller (1973), and Newmann (1973) examine ownership and performance of stock and mutual life insurance companies. They find that stock-owned life insurance companies perform better than mutually-owned companies. This is consistent with Williamson's (1963) *expense preference* hypothesis, in that mutual company management may operate to enhance perquisite compensation or otherwise engage in inefficient activities. Mutual company managers, less subject to monitoring and control by the market and by stockholders, will be less effective in minimizing costs; see Boose (1991) and Kroll, Wright, and Theerathorn (1993).

In demutualization announcements, companies typically list access to capital as a primary motive; see Bailey (1995), Goldstein and Avril (1998), and Dauer (1998). Empirical evidence that the need for capital and opportunity to control free cash flow motivate life-insurance company demutualizations is provided by Cole, McNamara, and Wells (1995), Carson, Foster, and McNamara (1998), and Butler, Cui, and Whitman (2000). Viswanathan and Cummins (2003) find significant support for the *access to capital* hypothesis among both life-health and property-liability insurers that have demutualized since 1981.

Demutualization has also been a topic of study in the banking industry. Masulis (1987) finds that conversion from a mutual savings bank to a stock-owned savings bank results in abnormal returns to shareholders. Jordan, Verbrugge, and Burns (1988) report similar results, finding that demutualizing thrifts tend to post abnormally high returns in the days following their IPOs. Carhill and Hasan (1997) find that over the long run, thrifts that demutualize experience poor performance that is driven primarily by the increased operational costs of stock-owned firms. Carter and Stover (1990) find that demutualization of savings and loans has little impact on managerial behavior.

Demutualizations impact a variety of factors of interest to individual investors and financial services professionals. Existing studies of demutualization, in either banking or insurance, do not examine the impact of demutualization on the competitive landscape of the relevant industry. In this paper, we examine the intra-industry effects of demutualization in the life insurance industry. We examine two relevant research questions. First, do life insurance company demutualizations impact the value of existing stock-owned life insurance companies? And second, do life insurance company demutualizations impact the value of existing stock-owned companies in other segments of the insurance industry?

There is a literature that examines the intra-industry effects of acquisition decisions. This methodology can be employed to study the issue at hand. For example, Bittlingmayer and Hazlett (2000) examine the response of the stock prices of Microsoft's competitors to the announcement of antitrust enforcement actions against Microsoft. They find that the competitors experience negative stock price reactions to the enforcement actions against Microsoft, casting doubt on the notion that Microsoft's actions are anticompetitive. Akhigbe and Martin (2002) examine whether acquisitions by Microsoft Corporation affect the stock prices of competitors in the computer industry. They report mixed results, depending on the business line of the acquisition.

Following Akhigbe and Martin (2002) we posit two potentially offsetting effects of intra-industry effects in response to demutualizations of life insurance companies. The *information effects* hypothesis posits that demutualizations signal favorable future industry conditions and/or the increased likelihood of future acquisitions in the industry [see also Song and Walkling (2000)]. Favorable industry conditions would benefit all life insurance companies, leading to a positive stock price reaction for existing stock-owned companies. The *competitive pressure* hypothesis posits that industry rivals will be negatively impacted by demutualizations if the conversion provides the former mutually-owned company a more efficient organizational form, increased access to capital, and increased competitiveness in the industry [see also Akhigbe and Martin (2000)].

The increased capital provided to life insurance companies from demutualization may also allow these firms to expand into other segments of the insurance industry. Announcements of demutualization by life insurers then may also signal information effects or competitive pressure to these other segments of the insurance industry.

III. DATA AND METHODOLOGY

III.1. DATA

We obtain a sample of demutualized life insurance companies by performing a search on Lexis/Nexis. We search for “demutualization” and “stock conversion” for the period 1996 through 2000. We focus on a relatively short and recent period that was characterized by increased competition, falling regulatory barriers, globalization, expanded used of the Internet, demographic changes, and a shift in product demand; see Optima (2000). This period allows us to examine the intra-industry effects of demutualizations during a short period of homogeneous industry conditions. The event date is defined as the date that the demutualization is first mentioned in the *Wall Street Journal*, or on Lexis/Nexis if not mentioned in the *Wall Street Journal*. The results of the search are summarized in Table 1. We find 13 life insurance companies that demutualized during this period with data available on CRSP and with announcement dates available either in the *Wall Street Journal* or on Lexis/Nexis.

Insert Table 1 about here

To examine the structure of the insurance industry, we gather data on competitors in the life insurance (SIC 6311) industry and in other segments of the insurance industry: accident and health (SIC 6321), hospital and medical service plans (SIC 6324), fire, marine and casualty (SIC 6331), surety (SIC 6351), title (SIC 6361), and insurance carriers (SIC 6399). A listing of all firms in the life insurance industry (primary SIC code 6311), with data available on Compustat, is contained in Table 2, along with data on total assets, net sales, and market capitalization for the year ended 2000. The result is a total of 54 companies, twelve of which demutualized in the 1996 to 2001 period and 42 stock-owned life insurance companies that existed prior to 1996.[2]

Insert Table 2 about here

Descriptive statistics on the demutualizing companies, the existing stock-owned companies, and the combined group are shown in Table 3. The twelve demutualizing companies have sales ranging from $813 million to $42,544 million. The 42 existing stock-owned companies have sales ranging from $5 million to $94,251 million. The twelve demutualizing companies have mean sales of $12,558 million and median sales of $8,150 million. The 42 existing stock-owned companies have mean sales of $7,082 million and median sales of $490 million. Overall, the demutualizing companies are larger than the existing stock companies, but the difference in means is not statistically significant.

Insert Table 3 about here

III.2. METHODOLOGY

To test the *information effects* and *competitive pressure* hypotheses, we compute cumulative abnormal returns for the stock-owned life insurance companies and the other stock-

[2] Only twelve demutualizing firms are shown here because Summit Life Corp. does not have data available on Compustat, but is included in the sample because it does have data on CRSP.

owned insurance companies around the announcement dates of the demutualizations. We use the standard event study methodology of Brown and Warner (1985) to compute the daily excess returns. We use a two-step procedure to compute the average daily abnormal returns with stock price data from CRSP.

First, we estimate the parameters of a single-factor market model for each firm. We use the returns for days -255 to -46 to estimate each firm's alpha and beta coefficients. As is standard in applying event-study methodology, we utilize an estimation period of approximately 200 trading days of returns. To limit the possibility of any estimation bias, we stop the estimation period at day -46, well in advance of the accumulation period.

Second, we compute the abnormal return on day t as:

$$AR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{1}$$

where,

N = the number of observations,

$AR_{it} = R_{it} - \alpha_i - \beta_i RM_t$,

R_{it} = the daily return for firm i on day t

α_i, β_i = parameters of the market model estimated over days -255 to -46 and

RM_t = the daily return on the CRSP equally-weighted index (including dividends) on day t.

Cumulative abnormal returns (CAR) are computed as:

$$CAR_{t_1, t_2} = \sum_{t=t_1}^{t_2} AR_t \tag{2}$$

where,

t_1 = the first day of the accumulation period, and

t_2 = the last day of the accumulation period.

We test the abnormal returns for statistical significance using a Z-statistic as described in Mikkelson and Partch (1988). The Z-statistic is computed as:

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \left[\sum_{t=t_1}^{t_2} AR_{it} \Big/ \sqrt{Var\left(\sum_{t=t_1}^{t_2} AR_{it}\right)} \right]. \qquad (3)$$

The denominator is the square root of the variance of the cumulative abnormal return of firm *i*. This variance is defined as:

$$Var\left(\sum_{t=t_1}^{t_2} AR_{it}\right) = V_i^2 \left[T + \frac{T^2}{ED} + \frac{\sum_{t=t_1}^{t_2} RM_t - T\left(\overline{RM}\right)^2}{\sum_{j=1}^{ED}\left(RM_j - \overline{RM}\right)^2} \right] \qquad (4)$$

where,

V_i^2 = the residual variance of firm *i*'s market model regression,

T = the number of days in the accumulation period (t_2-t_1+1),

ED = the number of days in the period used to estimate the market model, and

$\overline{RM}$ = the mean market return in the estimation period.

IV. RESULTS

In this section we present our results on the impact of life insurance company demutualization announcements on the value of stock-owned firms in the life insurance industry and on firms in other segments of the insurance industry. We find a negative and significant short-term announcement effect, offset by a larger long-term announcement effect. The results support both the *competitive pressure* and *information effects* hypotheses for both the life insurance industry and for the other segments of the insurance industry. Overall, the results are more supportive of the *information effects* hypothesis.

IV.1. IMPACT OF DEMUTUALIZATIONS ON OTHER STOCK-OWNED LIFE INSURERS

The event study results for the impact of life insurance company demutualizations on stock-owned competitors in the life-insurance industry are summarized in Table 4. Table 4 shows cumulative abnormal returns for several event windows. The results are shown for three long pre-event windows: (-30,-5), (-20,-5), (-10,-5); two short event windows: (-2,2), (-1,1); and six long post-event and event windows: (1,10), (1,20), (1,30), (-1,10), (-1,20), (-1,30).

Insert Table 4 about here

The announcement effects for the periods leading up to the demutualization announcement are not statistically different from zero. The announcement effect immediately around the announcement of demutualization (-1,1) is –0.65% statistically significant at the 5% level. The announcement effects for the longer periods subsequent to announcement (1,10), (1,20), and (1,30) are 0.67%, 2.30%, and 2.28% respectively, statistically significant at the 5%, 1%, and 1% levels respectively. Considering both the event-date and long-window post-event effects, the abnormal returns for windows (-1,10), (-1,20), and (-1,30) are 0.17%, 1.80%, and

1.78% respectively. The results for the first window are not statistically significant, while those for the two longer windows are significant at the 1% and 5% levels respectively.

The result showing a statistically significant negative announcement effect around the event date is consistent with the *competitive pressure* hypothesis, whereby demutualizing companies with a new organizational structure and increased access to capital lead to increased industry competition. The lager positive announcement effects in periods up to 30 days subsequent to the event day are consistent with the *information effects* hypothesis, whereby demutualization signals favorable future industry conditions and/or increased likelihood of future acquisitions in the industry. The overall reaction is also consistent with the *information effects* hypothesis.

IV.2. IMPACT OF DEMUTUALIZATIONS ON FIRMS IN OTHER SEGMENTS OF THE INSURANCE INDUSTRY

The event study results for the impact of life insurance company demutualizations on companies in other segments of the insurance industry are summarized in Table 5. Table 5 shows cumulative abnormal returns for several event windows. The results are shown for three long pre-event windows: (-30,-5), (-20,-5), (-10,-5); two short event windows: (-2,2), (-1,1); and six long post-event and event windows: (1,10), (1,20), (1,30), (-1,10), (-1,20), (-1,30).

Insert Table 5 about here

The announcement effects for the periods leading up to the demutualization announcement are not statistically different from zero. The announcement effect immediately around the announcement of demutualization (-2,2) is –0.41%, statistically significant at the 1% level. The announcement effect for the longer periods subsequent to announcement (1,10), (1,20), and (1,30) are 0.85%, 2.33%, and 2.57% respectively, statistically significant at the 5%, 1%, and 1% levels respectively. Considering both the event-date and long-window post-event effects, the abnormal returns for windows (-1,10), (-1,20), and (-1,30) are 0.68%, 2.15%, and 2.39% respectively. The results for the first window are not statistically significant, while those for the two longer windows are significant at the 1% level.

These results for other segments of the insurance industry are similar to the results for the life insurance industry. The period immediately around the demutualization announcement shows a negative stock price reaction, consistent with the *competitive pressure* hypothesis. The lager positive announcement effect in periods up to 30 days subsequent to the event day is consistent with the *information effects* hypothesis, whereby demutualization signals favorable future industry conditions and/or increased likelihood of future acquisitions in these other segments of the life insurance industry. The overall reaction is also consistent with the *information effects* hypothesis.

Taken together, the results show that there is significant information contained in demutualization announcements by life insurance companies. This information affects both stock-owned competitors in the life insurance industry and firms in other segments of the insurance industry in a similar fashion. The results are consistent with both the *competitive pressure* and *information effects hypotheses*. Given the larger and longer-term nature of the positive announcement effects, the results are more supportive of the *information effects* hypothesis. Life insurance company demutualizations signal favorable future industry conditions and/or increased likelihood of future acquisitions for all segments of the insurance industry.

V. SUMMARY AND CONCLUSION

The conversion of mutually-owned life insurance companies to stock-owned companies is a relatively recent phenomenon that represents an opportunity to better understand the causes and consequences of conversion along many dimensions. We examine one dimension of the demutualization of life insurance companies, the intra-industry effects. We examine two relevant research questions. Do life insurance company demutualizations impact the value of competing stock-owned life insurance companies? And, do life insurance company demutualizations impact the value of stock-owned companies in other segments of the insurance industry? We test two competing hypotheses of demutualization—the *information effects* hypothesis and the *competitive pressure* hypothesis.

We find that demutualization announcements are associated with a negative stock price reaction around the time of announcement for both existing stock-owned life insurance companies and for stock-owned companies in other segments of the insurance industry. This is consistent with the *competitive pressure* hypothesis. We find larger positive wealth effects for both groups of firms in the post-announcement period going out 30 days after the announcement. This is consistent with the *information effects* hypothesis. Overall, the results show that there is significant information contained in demutualization announcements by life insurance companies. Given the larger and longer-term nature of the positive announcement effects, the results are more supportive of the *information effects* hypothesis. Life insurance company demutualizations signal favorable future industry conditions and/or increased likelihood of future acquisitions for all segments of the insurance industry.

Active-minded investors may use these results to develop alpha-generating return strategies around life insurance demutualizations. Given the short-term negative stock-price reaction followed by the longer-term positive response, active investors can generate positive abnormal returns by longing publicly traded firms in the insurance industry following a demutualization announcement by a life insurer.

The results suggest that life insurance company demutualizations do signal changes in the competitive structure of the life insurance industry and in other segments of the insurance industry. A better understanding of these effects will provide useful information to investors seeking to evaluate the impact of organizational structure on demutualizing life insurance companies and on competitors in the insurance industry. Future research should focus on better understanding the nature of these effects and their long-term consequences.

REFERENCES

AFX News Limited, Asia (2003), "Japan's Mitsui Mutual to Convert to Stock Company in April 2004," www.afxnews.com, August 6.

Akhigbe, A. and A. D. Martin (2002), "Do Microsoft Acquisitions Benefit the Computer Industry?" Financial Analysts Journal, Vol. 58, 19-27.

Akhigbe, A. and A. D. Martin (2000), "Information-Signaling and Competitive Effects on Foreign Acquisitions in the U.S." Journal of Banking and Finance, Vol. 24, 1307-1321.

Bailey, S. (1995), "Advocates Hit Insurer's Plan to Demutualize," The Boston Globe, March 2, 33.

Bittlingmayer, G. and T. W. Hazlett (2000) "DOS Kapital: Has Antitrust Action Against Microsoft Created Value in the Computer Industry?" Journal of Financial Economics, Vol.55, 329-359.

Boose, M. A. (1990) "Agency Theory and Alternative Prediction for Life Insurers: An Empirical Test," Journal of Risk and Insurance, Vol. 57, 110-136.

Brown, S. J. and J. B. Warner (1985), "Using Daily Stock Returns: The Case of Event Studies," Journal of Financial Economics, Vol. 14, 3-32.

Butler, R. J., Cui, Y., and A. Whitman (2000), "Insurers Demutualization Decisions," Risk Management and Insurance Review, Vol. 3, 135-154.

Carhill, M. and I. Hasan (1997), "Mutual to Stock Conversion, Information Cost, and Thrift Performance," Financial Review, Vol. 32, 545-568.

Carson. J. M., M. D. Forster, and M. J. McNamara. (1998), "Changes in Ownership Structure: Theory and Evidence from Life Insurer Demutualizations," Journal of Insurance Issues, Vol. 21, 1-22.

Carter, R. B. and R. D. Stover (1990), "The Effects of Mutual to Stock Conversion of Thrift Institutions on Managerial Behavior," Journal of Financial Services Research, Vol. 4, 127-144.

Cole, C. S., M. J. McNamara, and B. P. Wells (1995), "Demutualizations and Free Cash Flow," Journal of Insurance Issues, Vol. 18, 37-56.

Dauer, A. C. (1998), "MONY Pleads Case for Going Public," Journal of Commerce, October 26, 8A.

Goldstein, J. and T. Avril (1998) "Prudential Plans Conversion to Publicly Traded Company," The Philadelphia Enquirer, February 13.

Jordan, B. D., J. A. Verbrugge, and R. M. Burns (1988), "Returns to Initial Shareholders in Savings Institution Conversions: Evidence and Regulatory Implications," Journal of Financial Research, Vol. 11, 125-136.

Kroll, M. P., P. Wright, and P. Theerathorn (1993), "Whose Interests do Hired Top Managers Pursue? An Examination of Selected Mutual and Stock Life Insurers," Journal of Business Research, Vol. 26, 133-148.

Masulius, R. (1985), "Changes in Ownership Structure: Conversions of Mutual Savings and Loans to Stock Charter," Journal of Financial Economics, Vol. 18, 29-59.

Mikkelson, W. H. and M. W. Partch (1988), "Withdrawn Security Offerings," Journal of Financial and Quantitative Analysis, Vol. 23, 119-134.

Newmann, S. (1973), "Ownership and Performance: Stock and Mutual Life Insurance Companies: Comment," Journal of Risk and Insurance, Vol. 40, 631-635.

Optima, 2000. "Demutualization in the Life Insurance Industry—A response to Shifting Industry Opportunities." Optima Investment Research September 26, 1-10.

Song, M. H. and R. A. Walkling (2000), "Abnormal Returns to Rivals of Acquisition Targets: A test of the 'Acquisition Probability Hypothesis,'" Journal of Financial Economics, Vol. 55, 143-171.

Spiller, R. (1973), "Ownership and Performance: Stock and Mutual Life Insurance Companies: Reply," Journal of Risk and Insurance, Vol. 40, 635-638.

Spiller, R. (1972), "Ownership and Performance: Stock and Mutual Life Insurance Companies," Journal of Risk and Insurance, Vol. 39, 17-26.

Smith, B. D. and M. Stutzer (1995), "A Theory of Mutual Formation and Moral Hazard with Evidence from the History of the Insurance Industry," Review of Financial Studies, Vol. 8, 545-577.

Viswanathan, K. S. and J. Cummins (2003), Ownership Structure Changes in the Insurance Industry: An Analysis of Demutualization," Journal of Risk and Insurance, Vol. 70, 401-437.

Williamson, O. E. (1963), "Managerial Discretion and Business Behavior," American Economic Review, Vol. 53, 1032-1057.

TABLE 1
Demutualizing Life Insurance Companies

Companies announcing a demutualization during the period 1996-2000, determined by a Lexis/Nexis search. Companies are in the Life Insurance industry—Primary SIC code 6311. Date is the first mention of demutualization in the *Wall Street Journal* or on Lexis/Nexis. Companies have required data available on CRSP.

Demutualizing Company	Announcement Date	Source
AmerUs Group Co.	12/1/98	*Wall Street Journal*
Canada Life Financial Corp.	4/2/98	Lexis/Nexis
John Hancock Financial Services, Inc.	5/13/98	*Wall Street Journal*
Manulife Financial Corp.	1/21/98	*Wall Street Journal*
Metlife, Inc.	3/6/98	*Wall Street Journal*
MONY Group, Inc.	9/9/97	*Wall Street Journal*
Nationwide Financial Services	10/28/96	*Wall Street Journal*
Phoenix Companies, Inc.	4/2/00	Lexis/Nexis
Principal Financial Group, Inc.	3/3/00	*Wall Street Journal*
Prudential Financial, Inc.	2/12/98	*Wall Street Journal*
Prudential PLC	6/15/00	*Wall Street Journal*
Summit Life Corp.	10/19/98	Lexis/Nexis
Sun Life Financial Services of Canada,	1/28/98	Lexis/Nexis

Distribution by Year	Number	Percent
1996	1	7.7%
1997	1	7.7%
1998	8	61.5%
1999	0	0.0%
2000	3	23.1%
Total	13	100.0%

TABLE 2
Assets, Sales, and Market Capitalization of Life Insurance Companies
(Primary SIC Code 6311)

All life insurance companies with data on Standard & Poor's Compustat are shown. Companies shown in bold are those that demutualized during 1996-2000. (Note: Only twelve demutualizing firms are shown here because Summit Life Corp. does not have data available on Compustat, but is included in the sample because it does have data on CRSP.) Amounts, in millions of dollars, are for year ended 12/31/00.

Company Name	Sales	Assets	Market Cap.
AEGON NV	$28,872.80	$229,269.98	$63,543.79
ALLSTATE LIFE INSUR CO/NY	$317.56	$3,502.51	na
AMERICAN INTERNATIONAL GROUP	$45,972.00	$306,577.00	$296,047.88
AMERICAN NATIONAL INSURANCE	$1,834.48	$9,270.39	na
AMERICO LIFE INC	$450.43	$4,241.15	na
AMERUS GROUP CO -CL A	**$813.39**	**$11,471.52**	**$1,384.73**
ANNUITY AND LIFE RE HLDGS	$307.15	$2,224.69	$814.41
AXA -SPON ADR	$94,250.83	$445,569.50	na
CANADA LIFE FINL CORP	**$4,979.08**	**$21,815.63**	**$4,837.61**
CITIZENS FINL CORP KY	$31.30	$135.54	$28.69
CITIZENS INC	$66.68	$267.84	$175.75
CONVERIUM HOLDINGS AG -ADR	$2,150.50	$8,321.30	na
COTTON STATES LIFE INSURANCE	$41.51	$211.30	$72.97
DELPHI FINANCIAL GRP -CL A	$512.89	$3,440.01	$1,291.84
ERIE FAMILY LIFE INS CO	$111.94	$1,020.34	$166.20
FBL FINL GROUP INC -CL A	$367.62	$3,704.05	$685.99
FINANCIAL INDS CORP	$44.42	$300.77	$81.79
FIRST ALLIANCE CP/KY	$4.48	$21.09	na
GLOBAL PREFERRED HLDGS -REDH	$30.04	$56.62	na
GREAT AMERN FINL RESOURCES	$824.30	$7,975.90	$1,178.58
GREAT-WEST LIFE & ANNUITY IN	$3,164.62	$27,897.39	$260.25
GUARDIAN LIFE INS CO OF AMER	$6,743.30	$32,359.30	na
HANCOCK JOHN FINL SVCS INC	**$7,454.30**	**$87,353.30**	**$12,634.93**
HARTFORD LIFE INSURANCE	$3,447.00	$138,835.00	na

CO			
ING GROEP NV -ADR	$46,926.86	$610,381.50	na
ING LIFE INS & ANNUITY CO	$1,654.30	$57,153.00	na
JEFFERSON-PILOT CORP	$3,238.00	$27,321.00	$8,946.01
KANSAS CITY LIFE INS CO	$472.91	$3,646.26	$466.59
LINCOLN NATIONAL CORP	$6,851.89	$99,844.06	$10,834.42
MANULIFE FINL CORP	**$9,437.97**	**$40,058.68**	**$16,019.06**
MAX RE CAPITAL LTD	$451.32	$935.50	na
MERRILL LYNCH LIFE INSUR CO	$507.48	$16,543.51	na
METLIFE INC	**$31,947.00**	**$255,018.00**	**$31,455.00**
METROPOLITN MTG & SEC - CL A	$171.42	$1,252.93	na
MONY GROUP INC	**$1,251.80**	**$24,575.30**	**$2,902.67**
NATIONWIDE FINL SVCS - CL A	**$3,170.30**	**$93,178.60**	**$6,830.35**
NATL WSTN LIFE INS CO -CL A	$292.72	$3,697.96	$360.93
NEW YORK LIFE INSURANCE	$21,996.00	$97,101.00	na
NORTHWESTERN MUTUAL LIFE INS	$16,529.00	$92,125.00	na
PHOENIX COMPANIES INC	**$2,898.60**	**$20,313.20**	**na**
PRESIDENTIAL LIFE CORP	$284.46	$2,982.43	$781.35
PRINCIPAL FINANCIAL GRP INC	**$8,845.80**	**$84,404.90**	**na**
PROTECTIVE LIFE CORP	$1,733.97	$15,145.63	$2,576.64
PRUDENTIAL FINANCIAL INC	**$26,544.00**	**$272,753.00**	**na**
PRUDENTIAL PLC -ADR	**$42,543.98**	**$231,727.72**	**na**
REINSURANCE GROUP AMER INC	$1,725.74	$6,061.86	$2,020.92
SCOTTISH ANNUITY & LIFE HLDG	$83.93	$1,178.50	$187.82
SOUTHERN SEC LIFE INS	$10.63	$77.13	$7.68
STANDARD MANAGEMENT CORP	$76.06	$1,470.46	$54.00
SUN LIFE FINL SVCS CDA INC	**$10,807.78**	**$37,214.36**	**$12,602.90**
THRIVENT FINL FOR LUTHERANS	$2,322.00	$22,112.00	na
TORCHMARK CORP	$2,515.89	$12,962.56	$5,741.27
UNITED TRUST GROUP INC	$35.75	$333.62	$28.43
YADKIN VALLEY BK & TR CO	$31.74	$371.90	$77.68

TABLE 3
Descriptive Statistics for Demutualizing and Existing Stock-Owned Life Insurance Companies (Primary SIC Code 6311)

All life insurance companies with data on Standard & Poor's Compustat are shown. Only twelve demutualizing firms are shown here because Summit Life Corp. does not have data available on Compustat, but is included in the sample because it does have data on CRSP.) Amounts, in millions of dollars, are for year ended 12/31/00.

Demutualizing Firms	Sales	Assets	Market Cap.
Number of firms	12	12	8
Maximum	$42,543.98	$272,753.00	$31,455.00
Minimum	$813.39	$11,471.52	$1,384.73
Mean*	$12,557.83	$98,323.68	$11,083.41
Median	$8,150.05	$62,231.79	$9,716.62

Existing Stock-Owned Firms	Sales	Assets	Market Cap.
Number of firms	42	42	25
Maximum	$94,250.83	$610,381.50	$296,047.88
Minimum	$4.48	$21.09	$7.68
Mean*	$7,082.33	$54,711.89	$15,857.27
Median	$490.20	$3,972.60	$466.59

All Firms	Sales	Assets	Market Cap.
Number of firms	54	54	33
Maximum	$94,250.83	$610,381.50	$296,047.88
Minimum	$4.48	$21.09	$7.68
Mean*	$8,299.11	$64,403.40	$14,699.97
Median	$1,609.02	$12,217.04	$1,178.58

* Differences in means are not statistically significant at the 10% level or better.

TABLE 4
Cumulative Abnormal Returns for Existing Stock-Owned Life Insurance Companies (Primary SIC Code 6311) Around the Announcement of Demutualization by a Mutually-Owned Life Insurance Company

Results are relative to first announcement of demutualization in either the *Wall Street Journal* or Lexis/Nexis for thirteen demutualization announcements occurring in 1996-2000. A market model is used to estimate abnormal returns.

Event Window	Number of Obs.	Mean Cumulative Abnormal Return	*z*-Stat.
Long-Window Pre-Event Returns:			
-30,-5	245	0.26%	-0.529
-20,-5	245	-0.56%	-1.608
-10,-5	245	-0.35%	-0.783
Short-Window Event-Date Returns:			
-2,2	245	-0.51%	-1.158
-1,1	245	-0.65%	-2.252**
Long-Window Post-Event and Event-Date Returns:			
1,10	245	0.67%	2.234**
1,20	245	2.30%	4.132***
1,30	245	2.28%	3.050***
-1,10	245	0.17%	1.260
-1,20	245	1.80%	3.364***
-1,30	245	1.78%	2.475**

*** Statistically significant at the 1% level
** Statistically significant at the 5% level
* Statistically significant at the 10% level

TABLE 5

Cumulative Abnormal Returns for Non Life Insurance Segments of the Insurance Industry (Primary SIC Codes 6321—Accident and Health, 6324—Hospital and Medical, 6331—Fire, Marine, and Casualty, 6351—Surety, 6361—Title, and 6399—Insurance Carriers) Around the Announcement of Demutualization by a Mutually-Owned Life Insurance Company

Results are relative to first announcement of demutualization in either the *Wall Street Journal* or Lexis/Nexis for thirteen demutualization announcements occurring in 1996-2000. A market model is used to estimate abnormal returns.

Event Window	Number of Obs.	Mean Cumulative Abnormal Return	*z*-Stat.
Long-Window Pre-Event Returns:			
-30,-5	1,014	0.62%	0.603
-20,-5	1,014	0.09%	-0.869
-10,-5	1,014	-0.38%	-1.403
Short-Window Event-Date Returns:			
-2,2	1,014	-0.41%	-3.281***
-1,1	1,014	-0.14%	-1.588
Long-Window Post-Event and Event-Date Returns:			
1,10	1,014	0.85%	2.221**
1,20	1,014	2.33%	6.192***
1,30	1,014	2.57%	4.905***
-1,10	1,014	0.68%	1.342
-1,20	1,014	2.15%	5.397***
-1,30	1,014	2.39%	4.329***

*** Statistically significant at the 1% level
** Statistically significant at the 5% level
* Statistically significant at the 10% level

ACTIVE VERSUS PASSIVE INVESTING - AN ANALYSIS OF UK EQUITY MARKETS, 1991-2005

Barnes, E.[1] and Scott, M.
University College Cork, Ireland.

ABSTRACT

This study examines the pattern of active versus passive trading in UK equities over the period 1991-2005. We describe a metric to analyse trading activity and volumes in the UK FTSE350 and AIM markets, with emphasis on industrial and size-based effects.[12,1] Our findings indicate that active stock picking has been consistently declining in the UK market over the period studied for all markets, size quintiles and in virtually every industrial sector. Moreover, trading patterns reveal a pronounced size effect with significantly less stock picking in larger capitalisation stocks vis-à-vis smaller stocks. Patterns of investment in the AIM suggest an increase in index trading over time but higher overall levels of stock picking relative to the FTSE350 list.

EFM Classification: 350, 370

[1] Address for Correspondence: Dr Edel Barnes, National University of Ireland, Cork, O'Rahilly Building, UCC, College Road, Cork, Ireland. Tel: +353 21 4902839. Email: e.barnes@ucc.ie.

I. INTRODUCTION

Theories of efficient markets, standard paradigms of academic and empirical finance, have clear implications for asset combination and diversification decisions. If markets are efficient and operate well, prices should reflect all available information regarding firms' financial position and future prospects and it should not be possible to beat the market other than by chance. Investors should only be able to earn abnormal returns by having access to private firm information, superior forecasting ability or through chance. In consequence, rather than incur the significant private costs of research to obtain proprietary information, investors should be as well off investing (passively) in a market index which includes a broad range of different securities. With this approach, the volume of trade in any particular stock should reflect the weight of that firm in the market portfolio/index, and market weighting should explain fully the variation in volume of trade.

However in a climate of low interest rates, as investors seek superior returns one might expect significant active investment as distinct from passive investment. This leads to an upsurge in the use of skill and research on the part of professional investors to identify mispriced securities and trade on that mispricing, a process which is costly and which offers no guarantee that benefits will outweigh the very substantial costs of information acquisition and trading. Carhart (1997) among others documents the magnitude of active vis-à-vis passive trading costs and notes that, in terms of net returns, actively managed investment funds have tended to under-perform their passively managed counterparts.[2] If the benefits of active fund management consistently fail to outweigh the costs passive investment is surely more constructive for investors.

Despite extensive empirical evidence on patterns in, and costs of active vis-à-vis passive trading, evidence largely relates to US markets and comparatively little research has been conducted into patterns of trading in UK markets. Given the global significance of the London market, we consider that an in-depth examination of active vis-à-vis passive trading patterns for the UK is merited, and that such evidence would represent an interesting increment to the body of literature at this point. The purpose of this study is to examine the pattern of active versus passive trading in UK equities over the period 1991-2005 inclusive. Drawing on the two fund separation theorem (Lo and Wang, 2000; Bhattacharya and Galpin, 2005) we describe a metric to analyse trading activity and volumes in the UK FTSE350 and AIM markets, with emphasis on industrial and size-based effects.[12,1]

Our findings indicate that active stock picking has been consistently declining in the UK market over the period studied for all markets, size quintiles and in virtually every industrial sector, which evidence is consistent with patterns of trading documented for the US and some other markets. Our findings in respect of UK trading patterns reveal a pronounced size effect with significantly less stock picking in larger capitalisation stocks vis-à-vis smaller stocks. Patterns of investment in the AIM suggest and increase in index trading over time but higher overall levels of stock picking relative to the FTSE350 list.

Our paper is structured as follows. The next section presents an analysis of the theoretical motivations for and empirical evidence pertaining to stock and index trading and is followed by section three which describes our sample and the methodology we apply. The fourth section outlines the results of our analysis together with a discussion of those results and their consistence with the extant literature. In our final section we identify some limitations of our analysis together with some avenues for further study, and conclude.

II. LITERATURE REVIEW

Carhart (1997) among others documents the magnitude of active vis-à-vis passive trading costs and notes that actively managed investment funds have tended to be substantially more costly for investors reducing net investment returns.[2] This author examines persistence in fund performance for equity mutual funds in the US for the period 1962-93 and finds that persistence is almost completely explained by common stock factors and investment expenses. Over the long term he concludes that there is no significant momentum effect (the benefit of continuing to hold last year's winning stocks, identified by Fama and French, 1996) and that expense ratios, transactions costs and turnover are negatively related to mutual fund performance.[4] Essentially his findings are not supportive of the existence of significant stock selectivity skills among mutual fund managers for the period of his study.

Jensen (1968) identified stock selection ability and diversification/ risk minimisation as separate fund management responsibilities and based on the Sharpe/Lintner CAPM model, examined fund managers' 'predictive ability' in an analysis of US fund managers over the period 1945-64, the regression intercept term or alpha representing stock selection ability.[9] His findings indicate that over the sample period the mean fund was unable to generate sufficient returns to cover trading costs and would not have outperformed a passive 'buy and hold' investment approach.

In light of the historically poor returns to active fund management, Gruber (1996) queries why investors choose to buy actively managed funds on finding that active management adds value but that fund charges exceed this value added.[8] Wermers (2000) re-examines the value-added by mutual fund managers based on hypothetical stocks-only funds and concludes that while such funds outperformed the CRSP on average for his study period with higher turnover funds doing relatively better, the net effect of transactions costs and non-stock holdings resulted in his sample funds underperforming a passive indexing approach by 1% per annum on average.[17] Grinblatt and Titman (1989, 1993) report mutual fund out performance consistent with Wermers' (2000) findings but their findings with respect to the substantial drag on net returns of actively managed fund transactions costs are consistent with Wermers.[6] A useful comment on the active versus passive debate is provided in Malkiel (2003).[13]

In summary the body of literature seems to indicate that active management does not justify the fees typically charged for this service. If the benefits of active fund management are consistently negligible or even negative, passive investment is surely more constructive for investors and one would expect to observe indexing as the dominant investment philosophy if markets truly are efficient. To date the main body of literature relating to *the prevalence of* active versus passive investors is not well developed. Such literature as exists regarding persistence in performance, efficient markets and mutual fund performance have been carried out in the US and typically on US data.

A Bhattacharya and Galpin (2005) paper incorporates an important contribution to the debate by developing a metric to measure indexing.[1] These authors collected share volume and shares outstanding data from CRSP for NYSE, AMEX and NASDAQ listed stocks for the period July 1962 – December 2004, and for 43 other markets around the world from DataStream for the period January 1995 – July 2004, in order to conduct cross sectional monthly regressions. The 43 non-US markets are classified as emerging markets (22) and developed markets (21). A key finding is that there appears to be more stock picking in emerging markets (maximum 63%) vis-à-vis developed markets (maximum 45%), which result is intuitive given the greater coverage of stocks and sounder institutional arrangements in developed markets. Important exceptions are Germany which appears to have more stock picking than one would expect for a developed country (maximum 71%) and Russia which appears to have surprisingly little stock picking (maximum 35%). Notably the maximum proportion of stock picking was lowest in the US with 29% and greatest in China (maximum 80%). A further key finding is that stock picking appears to be declining systematically around the world, with this decline being most pronounced in emerging markets although the US data reveal a decline to a low of 24% in the 2000s compared to an average level of stock picking in the late 1960s of 60%.

When these authors examine their US data more minutely some further trends and patterns are apparent. Consistent with the practicalities of indexing, the practice is significantly more extensive for S+P 500 vis-à-vis non-S+P 500 stocks although indexing appears to be gaining in popularity for both categories of shares. Share turnover is also relatively greater for the larger non-S+P 500 shares. At all points examined, indexing seems to be greater for NYSE-listed vis-à-vis AMEX-listed stocks and indexing in the NASDAQ resembled that in the AMEX in the 1980s but more closely resembled trading in the NYSE post-2000 at which time stock picking in NASDAQ-traded stocks started to decline noticeably. There has been a consistent decline in stock-picking over time in all three markets however, and an apparent size effect as there seems to be greater indexing in larger stocks across all the US markets examined. Furthermore, partitioning by age, the authors find less stock picking in older stocks vis-à-vis young firm stocks. Again stock-picking is observed to be in decline across firms of all ages and across the 10 Fama and French (1997) industry classifications, although the maximum proportion of stock picking is higher in telecommunications which the authors describe as 'exciting' relative to 'boring' utilities.

Bhattacharya and Galpin hypothesise that analysts have expertise in identifying mispriced stocks and pick stocks that others should pick later.[1] Using IBES data on analyst following they find, inconsistent with their priors, that investors conduct more stock picking in stocks that analysts do not pick and hypothesise that this seems plausible if by undertaking and acting on their own research analysts consequently reduce the payoff to stock picking on one's own account. Again stock picking appears to be in decline across both analyst-followed and non-followed stocks with indexing being more pronounced in stocks followed by greater numbers of analysts.

In light of findings that stock picking is declining across all markets and sub-divisions of the data studied, Bhattacharya et al. question the 'long-run steady state fraction of stock-pickers' and develop a model based on firm specific risks and payoffs, trading costs and the market price of risk (the market Sharpe ratio) which is then applied to US data for the period 1964-2004.[1] Their findings suggest that firm-specific risk has been increasing over time and that stock-picking has declined in tandem. At a long-run estimate of a 'net benefit to stock-picking' measure, they estimate a steady state maximum proportion of stock-picking of approximately 11%, at which level the authors predict that stock-picking will eventually settle in the US. The United Kingdom is one of the developed markets examined by Bhattacharya et al. (2005).[1] In terms of world rankings of stock picking, the UK ranks 9th (21st) over the period 1995-99 (2000-04) respectively with a maximum proportion of stock picking of 47% (51%) respectively. While the estimated differential is not large, it is nevertheless interesting that the UK is one of very few markets in which the extent of indexing actually declined over that period, in consequence of which we consider that a fuller exploration of trading patterns in the UK might yield noteworthy findings. We also perceive the potential to examine more closely the role of industry, and of firm age or establishment in light of the existence since 1995 of trading in the UK Alternative Investment Market (AIM). It is to this analysis that we now turn.

III. DATA AND METHODOLOGY

The main objective of our analysis here is to investigate, illustrate and explain any variation in the patterns of active vis-à-vis passive equity trading over the period 1991-2005 inclusive for the FTSE350 and AIM markets, and specifically to explore any trends in stock-picking versus indexing for the period. We seek to ascertain the extent to which trading volume is explained by stock picking in the UK, whether there is a size and/or industry effect in such trading and whether patterns that apply to the FTSE350 main list are also apparent in AIM trading. Our methodological approach is based on that of Bhattacharya and Galpin (2005).[1] Their metric draws on insights of Lo and Wang (2000) who in turn base their theoretical discussion on Tobin's (1958) two-fund separation theorem.[12,16] Briefly, if the two-fund separation theorem holds and everybody in the world indexes between a risk-free asset and a value-weighted proxy for the market portfolio, with no price changes between trades, share turnover for each stock defined as share trading volume scaled by number of shares outstanding, should be identical for all stocks in the portfolio. Essentially (dollar) trading volume in any stock i should be entirely explained by the market capitalization of that stock. Regressing share trading volume on number of shares outstanding for each stock would yield a beta of 1 and an R^2 =1 if all investment in the market is indexing. To the extent that R^2 differs from 1, there has been a deviation from indexing which could reflect either stock picking or alternative investment strategies such as indexing to an alternative market index, hedging derivative positions etc. Thus R^2 in the following regression

$$Ln(VOL)_i = \alpha + \beta_i Ln(NOSH)_i + \varepsilon_i \qquad [1]$$

represents the proportion/extent of indexing in a given market and ($1-R^2$) represents the *maximum* proportion of investment trading that can be explained by stock-picking. VOL is the monthly £ volume of shares traded scaled by market capitalisation, NOSH is the £ value of shares outstanding for each stock at the end of that trading month (adjusted for closely held shares). The intercept term α represents the log of turnover, and the regression coefficient β describes the relation between trading volume and shares outstanding. The error term may be interpreted as a measure of abnormal volume at the firm-level. It is important to note that our stock-picking metric represents the *maximum volume of shares traded* that can be explained by stock picking, as it implicitly assumes that investors are indexers or not. (R^2 will differ from 1 if agents either pick individual stocks in which to invest or alternatively index to tailored portfolios such as hedge funds of funds or exchange traded funds, which latter have enjoyed increasing popularity in recent times.) The metric does not distinguish between stock picking and the activities of hedge funds and funds of funds for example. However we consider that its appeal lies in its simplicity, understandability and ease of computation, requiring neither a highly quantitative background nor appreciation of complex statistics for its comprehension. It yields a measure which by default describes the extent of indexing in the market and in consequence allows us to infer trends in approaches to investment over the period studied.

Our analysis of the nature of stock trading activity in the UK centres on the FTSE350 list which we consider offers a happy medium between the small number of stocks that constitute the FT100 main list and the larger FTALLSH index which would present considerable data challenges. For comparative purposes we also analyse trading patterns for the newer AIM market which commenced trading in June, 1995 and which offers smaller firms an opportunity to access capital without the rigorous listing requirements of a full listing. Companies that list and enjoy share trading on the AIM are typically smaller and younger than those on the main list. For each month over the period January 1991 – December 2005 we obtain (aggregate) trading volume and NOSH data (at month end) for every firm in our sample and conduct monthly regressions as in equation [1] above. To be included in our sample a share must be on ordinary common share and be listed in its own country. There was some variation in the constituents of the 350 list, some companies disappearing over time and others not having obtained a listing until after the sample period commenced. We select at random 210 companies on which to base our analysis, representing 60% of the constituent firms at any point in time. These data were obtained from DataStream. For our size analysis we partition our sample companies into quintiles according to market capitalisation for every month, quintile 1 (5) containing the largest (smallest) stocks by market value respectively and we conduct difference of means tests on ($1-R^2$) measures to assess any size effect. For our industry analysis we base our analysis on the DataStream industry classifications (25). Some categories had fewer than 4 companies so we reclassified these firms under the 'other' classification, resulting in 17 distinct groupings for the FTSE350 sample. Codes ranging from 1-17 inclusive were accorded to each firm to facilitate our differentiation by industry. We do not seek to explore the existence of a size or industry effect in our AIM sample for which just 10 years of data were available January 1996 – December 2005 and we omit the period 1 June 1995 – 31 December 1995 to allow for market settling in this introductory trading period. Our metrics of key interest are R^2 and by extension $(1-R^2)$ which represent the proportion off indexing (maximum proportion of stock picking) respectively, though the intercept term which represents log of turnover also provides some useful hints about the absolute volume of trade in the various data sets. We conduct the Ryan-Joiner test of normality and the Durbin-Watson test for autocorrelation and find no non-stationarity in our data. Skewness is predictably a feature as turnover is necessarily bounded by 0 which induces positive skewness. We employ the White test for heteroskedasticity, again this is not a feature of our data though it might plausibly have been present in such time-series data. In consequence we utilise OLS and base our tests of significance on parametric P-values and (Fischer) F-statistics, and our t-statistics are of the 2-sided test of the null $\beta=1$.

As the error term in our cross-sectional regression represents a measure of abnormal volume at the firm level, we obtain monthly returns for each firm over the sample period from DataStream and relate them to this abnormal volume measure as follows:

$$R_{it} = \alpha + \beta(AVol)_{it} + \varepsilon_i \qquad [2]$$

where R_{it} is the firm-level return for firm i in month t, $AVol_{it}$ is abnormal volume from equation [1], α, β are regression coefficients and e_i the error term, to explore whether abnormal volume might have explanatory or predictive power for returns. Table I below describes our data for both FTSE350 and AIM companies at 31 December 2005, the end point of our sample period.

Table 1 about here

Clearly and unsurprisingly the mean FTSE350 firm is larger, enjoys significantly greater aggregate monthly trading volume and has significantly greater numbers of shares outstanding than its AIM counterpart. There is no minimum market capitalisation requirement for an AIM listing and the FTSE350 market has substantially greater market liquidity.

IV. RESULTS

Table 2 presents the results of applying equation [1] above to our FTSE350 data, where R^2 $(1-R^2)$ represent the proportions of indexing (maximum stock-picking) respectively. Our sample period pre(post)-dates that of Bhattacharya and Galpin (2005) by some 4 (1) years.[1] We are unclear about the specific stocks that constitute their UK list so that comparisons are somewhat problematic other than in general import and theme.

Table 2 about here

Throughout our beta value is greater than 1 at the 1% level so that while volume was approximately linear in NOSH an increase in shares outstanding resulted in a greater percentage change in the volume of trading with this effect being more pronounced through time. Our F-statistics suggest that the regression is highly significant in every period studied. R^2, the measure of proportionate indexing shows a clear trend upwards and there is a corresponding decline in the extent of stock-picking and other non-indexing trades, which accords both with our priors and with evidence for the US and other markets documented by Bhattacharya and Galpin (2005).[1] Our mean (maximum proportion of) stock picking at 31% appears lower than the median reported by Bhattacharya et al. of 49% and we report a systematic decline in stock picking over time while Bhattacharya reports a slight increase in stock-picking for the later years in his sample (to 51% for the 2000-4 period).[1] Our difference of means tests indicate that the level of indexing was significantly lower in 1991 relative to both the average over 1991-2005 (t-stat 21.62, p-value 0.000) and to the level recorded for 2005 at the end of our sample period (t-stat 24.61, p-value 0.000). These findings are consistent with those of Bhattacharya et al. (2005) who document a decline from 60% to 24% over the period 1960s-2000s for US markets.[1] Figure 1 below highlights this pronounced decline in stock picking over time for the FTSE350:

Figure 1 about here

Table 3 below presents the findings of our size analysis for quintiles of the FTSE350 where quintile 1 (5) represents the largest (smallest) stocks by market capitalisation respectively and metrics are mean values for the 1991-2005 period. For all quintiles the model statistics indicate significance at the 1% level and there is a clear size effect evident in the data with indexing being significantly greater in larger stocks vis-à-vis smaller ones. Difference of means tests confirm this size effect, (t-stat 22.05; p-value 0.000), and also that within each quintile there has been a systematic and significant decline in stock picking over time, a pattern that is evident in Figure 2 below.

Figure 2 about here

Table 3 about here

These findings are consistent with Bhattacharya and Galpin (2005), who document a similar size effect and time trend for US stocks.[1] We are unsurprised with these data, stock picking tends to be more prevalent in markets where there is less public disclosure of stock-specific information and analyst following (and consequent publication of price-sensitive information) is greater for larger capitalisation stocks. For our industry analysis we partition our FTSE350 stocks into the DataStream classifications as discussed in Section Three above. The mean number of companies per industry was 12.35 with a maximum (minimum) of 19 (4) respectively. Table 4 presents our findings with respect to these groupings for the period 1991-2005:

Table 4 about here

There is considerable variation in the relative dominance of each investment philosophy across industry type with stock picking in the Electrical and Utility (Chemical and Pharmaceutical) industries being significantly greater (less) than the mean. While not reported here, our ($1-R^2$) measures indicate a systematic decline in stock picking over the period studied for every industrial grouping. To an extent our findings are consistent with those of Bhattacharya and Galpin who report greater indexing in the 'boring' utility sector as do we, however we find no 'exciting' telecoms effect, stock picking in this UK sector having fallen over time rather than the reverse which appears to have been the US experience.

If analysts improve the information environment of the stocks they research and pick, thus reducing the benefits of stock picking, it seems intuitive that the returns to information gathering and in consequence stock picking will be greater in stocks that have less analyst following. In the UK stocks in the FTSE350 have widespread following but this is much less the case in AIM-listed stocks which tend to be smaller, younger, start-up enterprises without the trading history or visibility of larger stocks. Table 5 reports our indexing (non-indexing) metrics for AIM-listed stocks for the period 1996-2005 inclusive, the AIM having commenced trading only in June 1995.

Table 5 about here

In 1996, the first full year of trading in AIM-listed stocks thin trading would likely be a feature of the exchange and the concept of indexing substantially premature – formal indexing essentially became possible only from 01/1999 when approximately 320 firms were listed though AIM firm numbers were 500 from 2001. For the period as a whole, mean indexing is increasing albeit 2000 saw somewhat of a resurgence of the stock picking practice, which effect is likely due to the popularity of high-technology and start-up stocks at the time, a large number of which would have been listed on the AIM. Only towards the end of our sample period does volume traded approach linearity with shares outstanding, in the earlier years of the exchange's existence, volume traded fell substantially short of outstanding shares. When we compare indexing (non-indexing) in the FTSE350 with the AIM (for the period 1996-2005) our difference of means tests indicate that indexing was significantly greater (lower) in the FTSE350 (AIM) stocks overall and in each calendar year, and our intercepts suggest greater turnover in FTSE350 shares but more trading in larger AIM stocks vis-à-vis smaller ones. At the end of our sample period indexing in the FTSE350 averaged 79.5% compared with 45.8% for the AIM. From a practical perspective (and indexing is the practical manifestation or implementation of the tenets of modern portfolio theory) indexing is of course far easier for the FTSE350 stocks and would not have been possible before 1999 for the AIM. However both groups indicate a systematic trend upwards in indexing at the expense of stock-picking, which is more pronounced in the AIM, possibly because stock picking started at a substantially greater level, also because the decline in stock picking for the FTSE350, for which we have a longer time series of data, pre-dates this comparative period. It remains to be seen whether levels of stock-picking for these exchanges will converge over time or whether there is always likely to be somewhat less indexing in the AIM vis-à-vis the FTSE350, which pattern has been observed for the NASDAQ relative to the NYSE for the US market. There are substantial tax breaks available to investors that buy and hold AIM-listed stocks, which provide a disincentive to more active trading in individual shares. Figure 3 below depicts these trading patterns for UK markets for the period 1996-2005:

Figure 3 about here

In summary, we report here a significant decline in stock-picking for both FTSE350 and AIM markets over time, which results are robust to size and industry sector, and in general small capitalisation stocks are shown to attract greater stock picking activity than larger capitalisation stocks. While we do not undertake any systematic analysis of an abnormal trading volume association with firm returns, we identify this area as potentially yielding interesting research findings moving forward.

V. SUMMARY

In efficient markets asset prices fully reflect all available firm-specific information and it should not be possible to beat the market other than by chance. If asset prices do not reflect all relevant information, it may be possible to earn superior returns by undertaking research to identify value-relevant firm information and taking action thereon. The purpose of this study was to examine the pattern of active versus passive trading in UK equities over the period 1991-2005 inclusive. Our metric to analyse trading activity and volumes on the UK FTSE350 and AIM markets draws on the two fund separation theorem (Lo and Wang, 2000; Bhattacharya and Galpin, 2005), and we explore industrial and size-based effects.[12,1] Our findings indicate that active stock picking has been consistently declining in the UK market over the period studied for all markets, size quintiles and in virtually every industrial sector, although the AIM did see a brief resurgence of stock picking around 2000-1 at the height of the dot-com investment bubble. Moreover, trading patterns in the larger capitalisation FTSE350 list reveal a pronounced size effect with significantly less stock picking in larger capitalisation stocks vis-à-vis smaller stocks. Patterns of investment in the AIM suggest an increase in index trading over time but higher overall levels of stock picking relative to the FTSE350. This is likely due to the shorter history of the AIM and the characteristics of stocks traded thereon; however it will be interesting to observe whether trading patterns converge with those of the FTSE350 as has been observed for the NASDAQ vis-à-vis the NYSE markets, when we have a longer time series of data for the AIM. Our results are not especially surprising and are largely consistent with those of Bhattacharya and Galpin (2005) although we do report a level of stock picking for our FTSE350 that is substantially less than that which BG report for their undefined UK market.[1] If our constituent stocks are on average larger than theirs, taken in conjunction with our pronounced size effect there may be a resolution of the differential here. We fail to find any well-defined 'excitement/boredom' factor in patterns of industrial trading, though we report the greatest relative extent of indexing in the Chemical and Pharmaceutical sector which is characterised in the UK by relatively small numbers of large capitalisation stocks.

The evolution of the estimated stock picking impact over time is an issue which merits some consideration. The period covered by our study spans several cycles in the market from recession through recovery and expansion and back to recession from which a further recovery eventually materialised in the early years of this century. Over the period, many economic and geo-political events occurred which may well have influenced investor behaviour for which our statistics proxy. Throughout that period there has been a pronounced and consistent decline in active stock-picking at the expense of passive investment, and we remind ourselves that our stock-picking metric includes all non-indexing behaviour. Essentially and notwithstanding developments such as the introduction of ETFs and the increasing activity of hedge funds, active investment appears to be in decline. Whether this decline continues or whether stock picking will eventually settle at some 'long run steady state level' remains to be seen. Was this level, if it emerges, to be significantly lower than the mean level we report at the end of our sample, such a development would have serious implications for financial activity in The City and for a fund management industry which has exhibited unprecedented growth in the past decade.

We recognise the simplistic nature of the BG metric we compute in respect of stock picking in that it essentially measures all 'non-indexing' investment behaviour.[1] An interesting avenue for further study involves a more granular exploration of the impact if any of Exchange Traded Funds on investors' decision choices and whether this relatively low-cost investment approach which amplifies the net returns differential between indexing vis-à-vis active investment has substantially hastened the observed decline in stock-picking. These are themes which we hope to pursue moving forward.

Table I: Descriptive Statistics

Market		**FTSE350**		**AIM**
No. of Companies		210		500
Mean MV £m		6,778.5		31.3
Mean Volume 000s		150.75		3.69
Mean NOSH 000s		1205.55		155.76
Variables	**Ln(VO)**	**Ln(NOSH)**	**Ln(VO)**	**Ln(NOSH)**
No of obs.	37800	37800	59760	59760
Mean	10.251	12.814	5.762	10.451
Median	10.246	12.777	5.929	10.360
SE (Mean)	0.009	0.007	0.01	0.007
Std. Deviation	1.605	1.264	2.539	1.53
Minimum	1.569	8.509	2.302	2.303
Maximum	16.56	18.04	14.17	17.52
Skewness	-0.02	0.26	-0.31	0.01
Kurtosis	2.96	3.09	2.88	3.17
Durbin-Watson	1.87	1.91	1.89	1.88
Ryan-Joiner	0.999	0.997	0.997	0.996

MV=Market Capitalisation; Volume=aggregate volume of shares traded per month; NOSH=number of shares outstanding at end of calendar month, statistics presented are averages across all shares in each list respectively at 31 December, 2005.

Table 2: (Maximum Proportion of) Stock Picking in the FTSE350

Year	R^2	$(1-R^2)$	F-stat	Beta	P-value
1991-2005	69.1	30.9	505.89	1.09	0.000
1991	53.9	46.1	158.62	1.01	0.000
1992	52.7	47.3	165.05	1.03	0.000
1993	60.1	39.9	234.9	1.02	0.000
1994	61.4	38.6	256.18	1.02	0.000
1995	59.1	40.9	236.67	1.03	0.000
1996	64.2	35.8	298.55	1.06	0.000
1997	67.4	32.6	372.81	1.08	0.000
1998	67.0	33.0	393.4	1.06	0.000
1999	72.5	27.5	525.17	1.11	0.000
2000	78.3	21.7	737.91	1.12	0.000
2001	78.3	21.7	764.16	1.16	0.000
2002	82.0	18.3	953.14	1.19	0.000
2003	81.1	18.9	895.42	1.19	0.000
2004	79.2	20.8	789.05	1.16	0.000
2005	79.5	20.5	807.28	1.12	0.000

Model: $Ln(VOL)_i = \alpha + \beta_i Ln(NOSH)_i + \varepsilon_i$

Vol = £ volume of shares traded; NOSH = number of shares outstanding; measures are mean annual results based on monthly regressions described by the model.

Figure 1: Stock Picking in the FTSE350 1991-2005.

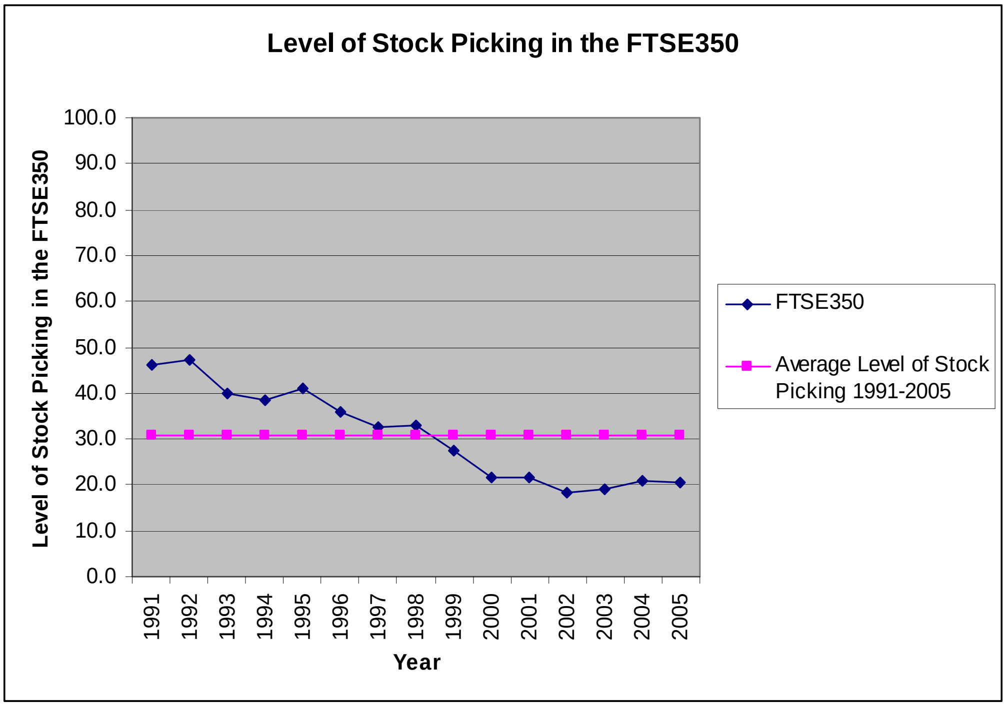


Figure 2: (Maximum Proportion of) Stock Picking in the FTSE350 1991-2005.

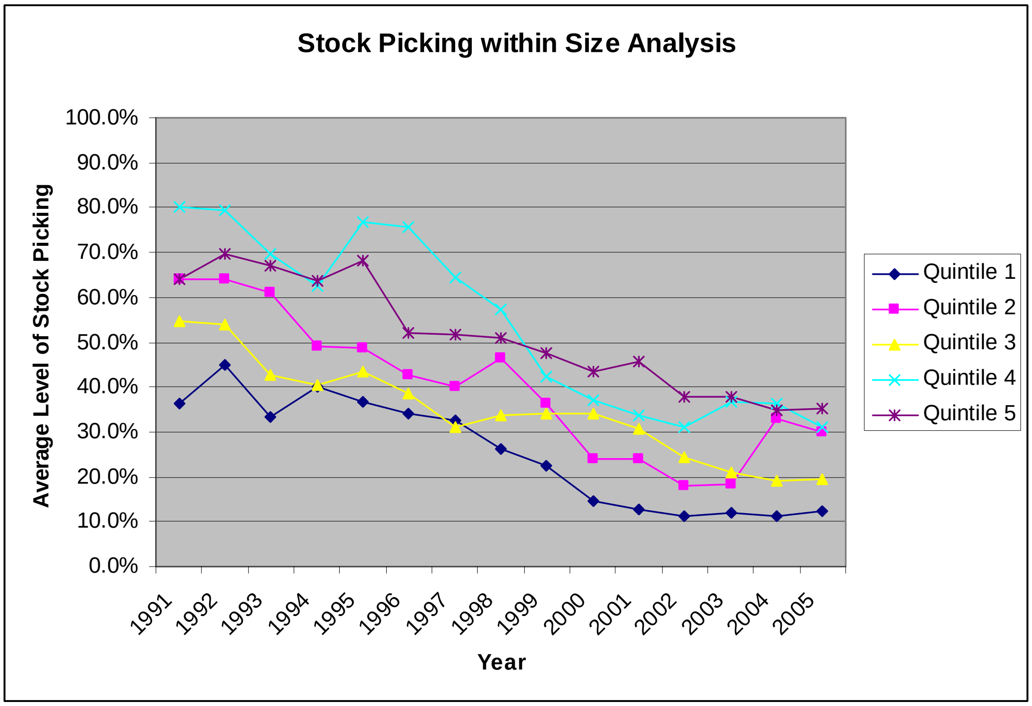


Table 3: (Maximum Proportion of) Stock-Picking in the FTSE350 by Market Capitalisation, 1991-2005.

Quintile (1991-2005)	R^2	$(1-R^2)$	F-stat	Beta	P-value
1	74.61	25.39	160.89	1.06	0.000
2	60.03	39.97	75.78	1.06	0.000
3	65.25	34.75	82.83	1.06	0.000
4	45.70	54.30	43.53	0.94	0.000
5	48.70	51.30	40.36	1.12	0.000

Model: $Ln(VOL)_i = \alpha + \beta_i Ln(NOSH)_i + \varepsilon_i$

Vol = £ volume of shares traded; NOSH = number of shares outstanding; measures are mean annual results based on monthly regressions described by the model.

Table 4: (Maximum Proportion of) Stock Picking in the FTSE350 by Industry

Industry	R^2	$(1-R^2)$	Beta	F-stat	P-value	Rank
Electrical + Utilities	29.46	70.54	0.72	734.15	0.000	1
Real Estate	44.19	55.81	1.65	284.18	0.000	2
Equity Investment	48.88	51.12	0.74	146.41	0.000	3
Other*	51.0	49.0	1.00	102.58	0.000	4
Telecoms	56.84	43.16	0.60	124.0	0.000	5
Aero Defence	57.40	42.60	0.80	68.28	0.000	6
Computers	59.63	40.37	0.82	913.31	0.000	7
Food, Drugs, Retail	62.32	37.68	0.95	167.34	0.000	8
Food Producers	64.32	35.69	1.30	76.67	0.000	9
Household G+S	67.56	32.44	1.31	191.87	0.000	10
Support Services	69.62	30.38	1.27	350.05	0.000	11
Engineering, Transport	72.25	27.75	0.90	133.34	0.000	12
Travel + Leisure	77.13	22.87	1.19	238.64	0.000	13
Insurance	77.54	22.46	1.25	78.40	0.000	14
Media	77.77	22.23	1.33	263.41	0.000	15
Banks + Gen Finance	78.02	21.98	1.18	120.43	0.000	16
Chemical, Pharmaceutical	83.26	16.71	0.91	205.91	0.000	17

Model: $Ln(VOL)_i = \alpha + \beta_i Ln(NOSH)_i + \varepsilon_i$

Vol = £ volume of shares traded; NOSH = number of shares outstanding; measures are mean annual results based on monthly regressions described by the model. Other* classification includes 40 companies from the following industries; auto and parts, beverages, tobacco, Personnel, H/C and Services, Mining, Construction, for which there were fewer than 4 firm-industry observations.

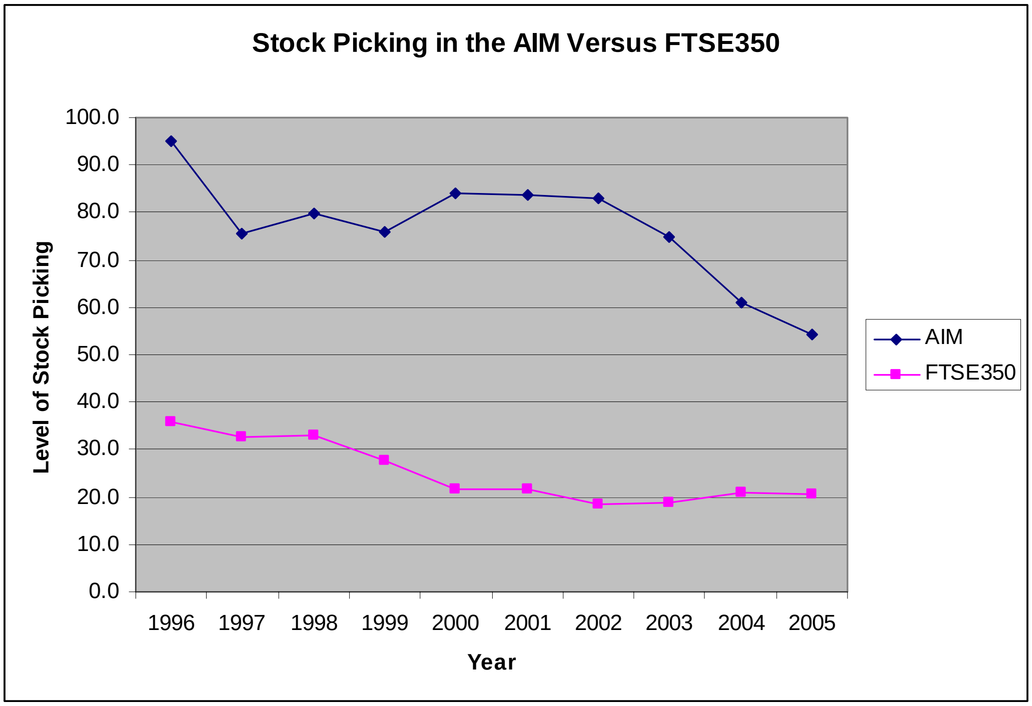
Table 5: (Maximum Proportion of) Stock Picking in the AIM 1996-2005.

Period	**R^2**	**$(1-R^2)$**	**F-stat**	**Beta**	**P-value**
1996-2005	23.0	77.0	164.80	0.754	0.000
1996	1.6	98.4	10.79	0.192	0.591
1997	24.6	75.5	38.85	0.788	0.000
1998	20.3	79.7	47.96	0.73	0.000
1999	24.2	75.8	79.74	0.851	0.000
2000	16.0	84.0	76.31	0.626	0.050
2001	16.3	83.7	90.83	0.686	0.000
2002	17.0	83.0	87.99	0.716	0.000
2003	25.0	75.0	135.32	0.851	0.000
2004	39.1	60.9	233.48	1.043	0.000
2005	45.8	54.2	292.25	1.156	0.000

Model: $Ln(VOL)_i = \alpha + \beta_i Ln(NOSH)_i + \varepsilon_i$

Vol = £ volume of shares traded; NOSH = number of shares outstanding; measures are mean annual results based on monthly regressions described by the model.

Figure 3: (Maximum Proportion of) Stock-Picking in the FTSE350, AIM for the period 1996-2005 inclusive.



REFERENCES

Bhattacharya, U and Galpin, N. (2005). "Is Stock Picking Declining Around the World?" AFA 2007 Chicago Meetings Paper, available at SSRN: http://ssrn.com/abstract=849627

Carhart, M. (1997). "On Persistence of Mutual Funds." *The Journal of Finance*, Vol. 52, No. 1, 57-82.

Economist. (2006) "Passive Aggression; Americas Shareholders Settle for Guaranteed Mediocrity:" January, 76, and "Alpha Betting", September 16th, 85.

Fama, E and French, K. (1996). "Multifactor explanations of asset pricing anomalies." *Journal of Finance* Vol. 51, 55-84.

Grinblatt, M. and Titman, S. (1989). "Mutual Fund Performance: An analysis of quarterly portfolio holdings." *Journal of Business,* Vol. 62, 394-415.

Grinblatt, M. and Titman, S. (1993). "Performance measurement without benchmarks: An examination of mutual fund returns." *Journal of Business,* Vol. 66, 1977-1984.

Grossman, S. and Stiglitz, J. (1980). "On the Impossibility of Informationally Efficient Markets." *The American Economic Review*, Vol. 70, No. 3, 393-408.

Gruber, M. (1996). "Another Puzzle: The Growth in Actively Managed Mutual Funds." *The Journal of Finance*, Vol. 51, No.3, 783-810.

Jensen, M. (1968). "The Performance of Mutual Funds in the Period 1945-1964." *The Journal of Finance*, Vol. 23, No. 2, 389-416.

Karpoff, J.M. (1987). "The Relation between Price Changes and Trading Volume: A Survey". *Journal of Financial and Quantitative Analysis* Vol. 22, No. 1, 109-126.

Lintner, J. (1965). "Security Prices, Risk and maximal Gains from Diversification." *Journal of Finance, XIX,* 587-616.

Lo, A. and Wang, J. (2000). "Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory." *The Review of Financial Studies*, Vol. 13, No. 2, 257-300.

Malkiel, B.G. (2003). "The Efficient Markets Hypothesis and its Critics". *European Financial Management*, Vol. 9, No. 1, 1-10.

Markowitz, H. (1952). "Portfolio Selection." *The Journal of Finance*, Vol. 7, No. 1, 77-91.

Sharpe, W. (1964). "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk" *Journal of Finance, XIX,* 425-442.

Tobin, J. (1958). ‘Liquidity preference as behaviour towards risk. *Review of Economic Studies* 25, 65-86.

Wermers, R. (2000). “Mutual fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs and Expenses.” *Journal of Finance* Vol. 55, No.4, 1655-1695.

FINANCIAL DISTRESS COMPARISON ACROSS THREE GLOBAL REGIONS

Harlan D. Platt
Northeastern University

Marjorie B. Platt
Northeastern University

ABSTRACT

Globalization has precipitated movement of output and employment between regions. We examine factors related to corporate financial distress across three continents. Using a multidimensional definition of financial distress we test three hypotheses to explain financial distress using historical financial data. A null hypothesis of a single global model was rejected in favor of a fully relaxed model which created individual financial distress models for each region. This result suggests that despite other indications of worldwide convergence, international differences in accounting rules, lending practices, managements skill levels, and legal requirements among others has kept corporate decline from becoming commoditized.

I. INTRODUCTION

As companies move production offshore they face a growing risk of supply-chain disruption caused by the possible financial distress of foreign suppliers. Receiving a 12 month early warning of impending supplier difficulties provides buying companies the opportunity to either remediate the supplier's condition or to contract with another supplier. The choice of actions may depend upon the capacity utilization in that particular sector or the availability of other suppliers. A supplier early warning system for manufacturing firms is analogous to bankruptcy models that alert lenders or investors that an offending firm is unable to service its long-term debt. Unlike investment analysts for whom obtaining advance warning of bankruptcy is sufficient, corporate purchasers require advance warning of supplier *financial distress*, a condition which normally precedes bankruptcy by some period of time.

There has been substantial bankruptcy prediction research; in contrast, few analysts have created models to forecast financial distress. In this globally connected world it is essential that there be a framework for evaluating financial distress risk. Platt and Platt (2006) recently developed a financial distress model for U.S. based companies that demonstrated an ability to predict the onset of financial distress for a sample of companies in manufacturing industries. No similar model exists for companies in other global regions. Globalization blurs international differences between countries. Are these similarities limited to areas such as technological adoption, arts and culture, and cuisine? Or, are business practices essentially universal now. This paper looks at one area, financial distress, where similarities may exist between global regions. Three global regions are considered: Asia (including Australia), Europe and the US. Profound differences between regions in accounting rules, legal practices, environmental laws, and business practices among others may limit the degree of convergence in the area of financial distress. This paper explores that question by developing a financial distress model across three global regions.

II. LITERATURE REVIEW

Bankruptcy has been rigorously studied since the pioneering work of Beaver (1966). Altman (1968) and Ohlson (1980) accelerated interest in the field by applying standard statistical techniques to predict bankruptcy outcomes. More recent innovations (Altman, Marco and Varetto, 1994; Yang, Platt and Platt, 1999; and Shumway, 2001) have extended the field by introducing newer methodologies. While there are variations across models, factors that often are found to be predictive of bankruptcy filings include debt load, profitability, liquidity, operating performance and growth.

A company either files for Chapter 11 bankruptcy protection from creditors because it finds itself in a difficult financial, operating or legal situation or is forced to do so by creditors because the firm's performance is so deficient that it can no longer honor commitments made to lenders. Regardless of the initiating event, companies in bankruptcy must work through the courts to restructure their operations and/or financial structure to emerge from the process as a viable company. Companies in financial distress, by contrast, are not yet so severely disabled that legal recourse is required. Often, companies in financial distress do take steps to remedy their precarious situation, including hiring turnaround managers, disposing of assets, and improving working capital management (See Hofer, 1980).

The literature focusing on financial distress tends to examine financial restructurings (John, Lang and Netter, 1992; Gilson, John & Lang, 1990; Wruck, 1990; Brown, James & Mooradian, 1992, and Asquith, Gernter and Scharfstein , 1994) or management turnover during distress

(Gilson, 1989). John *et al*. (1992) note that failing firm managers are replaced despite their delivering performance on par with their peers; in contrast, Asquith, *et al.* (1994) observe that distressed firm's managers underperform peers. Inconsistencies between studies may result from using samples drawn over different time periods or comprised of different firms.

Most prediction studies with the words "financial distress" in their title actually model bankruptcy, see (Frydman, Altman and Kao, 1985; Theodossiou, Kahya and Philippatos, 1996; Lin, Ko and Blocher, 1999). True models of financial distress are far less common [See Schipper (1977); Lau (1987); Hill *et al*. (1996); Platt and Platt, (2002)]. Schipper (1977) examined private colleges with imbalanced finances, Lau (1987) and Hill *et al*. (1996) moved beyond just bankruptcy to consider multiple states of corporate decline including financial distress, and Platt and Platt (2002) modeled financial distress among auto suppliers. More recently Platt and Platt, (2006) built a multi-industry model of financial distress for U.S. companies. Their most interesting finding was that bankruptcy and financial distress are not simply two sequential steps in the same process. Instead companies experience financial distress following poor operating results or as a consequence of external forces while bankruptcy is an action companies take to protect their assets often as a result of balance sheet issues.

Perhaps the reason that financial distress is studied less frequently than bankruptcy is that financial distress lacks a specific definition while formal bankruptcy, by contrast, takes place in a court of law and has a definite start date. It is unclear when financial distress begins or ends or even, for that matter, what it is. Moreover, there are various degrees of financial distress ranging from companies bordering on bankruptcy to those that are less troubled. Researchers have adopted a variety of financial distress definitions. Some are multidimensional so that only severely distressed firms are included while others are more narrowly defined. The best known academic descriptions of financial distress are:

- Evidence of layoffs, restructurings, or missed dividend payments, used by Lau (1987).
- A low interest coverage ratio, used by Asquith, Gertner and Scharfstein (1994).
- Cash flow less than current maturities of long-term debt, used by Whitaker (1999).
- The change in equity price or a negative EBIT, used by John, Lang, and Netter (1992).
- Negative net income before special items, used by Hofer (1980).

Platt and Platt (2006) adopt a multidimensional interpretation of financial distress in which they denote a firm as financially distressed only when it meets three of the criteria noted above. These three measures are:

- Negative EBITDA interest coverage (similar to Asquith, Gertner and Scharfstein (1994)).
- Negative EBIT (similar to John, Lang, and Netter (1992)).
- Negative net income before special items (similar to Hofer (1980)).

To be included as financially distressed a company needed to fail all three tests in two consecutive years. Companies classified as not financially distressed did not meet any of the three criteria in the two consecutive years. Interestingly, the negative EBITDA to interest coverage and the negative EBIT measures are less correlated than one might expect.

All three screens are correlated, but not perfectly, with correlation coefficients ranging from 0.38 (not significant) to 0.98 (highly significant). As a result, by using the intersection of three separate financial distress definitions fewer firms are labeled as financially distressed than would be the case with any single screen (Platt and Platt, 2006). That is, it is less likely that a non-financially distressed company is labeled as financially distressed when the intersection of three screens is employed. The use of three screens provides a multidimensional view of which companies are financially distressed. This definition appeals to purchasers high up the supply-chain who may be reluctant to confront a long-time supplier with an inaccurate financial distress accusation.

Given the success of Platt and Platt (2006) in modeling financial distress using US manufacturing companies and given the exponential growth in manufacturing worldwide, this study examines the question of whether factors (i.e., financial ratios) found to predict financial distress in the US also predict financial distress in Europe and in Asia. There are many reasons why it may be necessary to search for different financial ratios than those used by Platt and Platt (2006) to model financial distress in Europe or Asia. For example, differences in industrial development, technological adoption, manufacturing strategies, and access to capital markets could conceivably affect a firm's financial decisions and influence its resulting financial ratios.

This study relies on accounting information to distinguish between companies that are not financially distressed and those that might succumb to financial distress. Another concern is that differences in international accounting standards may affect our ability to characterize companies (See PricewaterhouseCoopers, 2001). For example, both US GAAP accounting and the International Accounting Standard (IAS) allow LIFO and FIFO treatment of inventories; in contrast, UK GAAP only allows the FIFO standard. Likewise, US GAAP accounting has four specific criteria used with revenue recognition while the other two accounting standards use fewer criteria. Accounting differences themselves will not lead to financial distress though their application may obfuscate international data comparisons. We controlled for this issue in two ways. First, we made certain that the distribution of ratios utilized in our study were similar across global regions. Second, qualitative (dummy) variables tested for uncontrolled regional variation.

Our research hypothesis expressed as a null hypothesis, is:

H_0: A global model will accurately predict financial distress in manufacturing companies in the US, Europe and Asia.

The alternate hypothesis has two variations. The first is:

H_a: A global model exists in which there are commonalities across regions in how factors affect financial distress though there are broad regional differences.

The second alternate hypothesis is:

H_b: There is no global model of financial distress. Different processes entirely explain financial distress in various locations.

Being unable to reject H_0 would allow for a single explanation of how firms succumb to financial distress in different locations. Not being able to reject H_a, the first variation of the alternate explanation, would modify the single global model with differential regional intercepts and slopes as needed while seeking to maintain the maximum degree of similarity across regions. Finally, not rejecting H_b would relax all constraints so that the explanation of financial distress on each region would have separate factors explaining that region's financial distress process.

III. METHODOLOGY

Data

Financial data from 1999 – 2001 for US companies were obtained from S&P's Research Insight Compustat Database. Comparable data from audited financial statements for European and Asian companies were obtained from the S&P's Research Insight Global Vantage Database. Only companies surviving throughout the three year period are included in the sample. This data was divided into two groups: just 1999 and then both 2000 and 2001. Methodologically we followed a two step procedure. In the first step, the 2000 and 2001 data were used to categorize companies by status: financially distressed and non-financially distressed. Companies were placed in the financially distressed group when they failed three tests for financial distress in both years. By contrast, a company was categorized as non-financially distressed if all three metrics (EBDITDA to interest coverage, EBIT, and net income before special items) were positive in both 2000 and 20001. Then financial ratios were created with the earlier data from 1999. These ratios were used in the second step to predict financial distress among companies (both financially distressed and non-financially distressed) whose performance in 2000 and 2001 was reviewed in the first step. The two year gap between the year when companies are classified as financially distressed or not and the data used to explain that classification is necessary so that companies are not classified and modeled with the same data or ratios. Table 1 contains the composition of sample firms used to build the statistical models by region and industry. Table 2 contains individual items and ratios used to bifurcate the sample into financially distressed and non-financially distressed groups with the means and medians of the three screening metrics by region, financial status for the largest industry classifications in the sample. Table 2 demonstrates that the three metrics clearly differentiate between the two sample groups, non-financially distressed versus financially distressed companies. Like other researchers in this area, we did not track companies in years beyond 2001 to determine their future status.

Insert Tables 1 and 2 about here

Dependent Variable: Financial Distress Defined

Following Platt and Platt (2006), we adopt a multidimensional interpretation of financial distress in which a firm is categorized as financially distressed only when it meets all three of the following criteria for two consecutive years:

- Negative EBITDA interest coverage (similar to Asquith, Gertner and Scharfstein (1994)).

- Negative EBIT (similar to John, Lang, and Netter (1992)).
- Negative net income before special items (similar to Hofer (1980)).

By using the intersection of three separate financial distress definitions fewer firms are labeled as financially distressed than would be the case with any single screen. That is, it is less likely that a non-financially distressed company is labeled as financially distressed when the intersection of three screens are employed; though, as a consequence, more financially distressed companies may be incorrectly described This outcome is preferred when the cost of misidentifying a non-financially distressed company as financially distressed is higher than the alternative misclassification. Financially distressed firms were defined as those that had negative values for the three screening criteria in both 2000 and 2001. A two year approach was followed to avoid calling as financially distressed companies having just a single bad year. By contrast, non-financially distressed firms were defined as those whose three screen metrics were positive for both years.

Independent Variables

Table 3 contains the financial ratios that were tested as independent variables for modeling purposes. The financial ratios represent measures of profitability, financial leverage, liquidity, operating efficiency and growth, all of which are factors frequently included in models predicting either financial distress or bankruptcy.

Insert Table 3 about here

A common problem in empirical studies occurs when information is drawn from companies across many industries in order to create a larger sample. The problem created by that decision is that the sample mean value of financial ratios may then vary depending on the mix of industries from which sample firms are drawn. In other words, another sample is likely to have different sample mean values and different coefficient estimates. The industry-relative framework pioneered by Altman and Izan (1984) and later used and rationalized by Platt and Platt (1990, 1991) mitigates this problem. The industry-relative framework transforms data to be relative to the industry's average value. The transformation of company ratios into industry-relative ratios is described in equation (1).

$$\text{Industry - Relative Ratio}_{\text{i,j}} = \frac{\textit{Firm i's Ratio } (r)}{\textit{Mean Ratio in Industry}_{\;j}} * 100 \qquad (1)$$

where firm i is a member of industry j and 100 adjusts percentage ratios to scalar values greater than 1.0. The transformation starts with a company's ratio and then divides that quotient by the value of that same ratio for the average firm in the industry. The industry relative data adjustment is also performed in this study for each continent separately.

Model Development, Specification and Comparison

A global model of financial distress (Model 1) is developed using financial ratios contained in Table 3. Companies from the three regions are pooled together. Data are drawn from a firm's 1999 fiscal year.[1] Initially, one ratio from each group in Table 3 was selected to minimize potential multicollinearity. Because several variables in each category could potentially discriminate between the two groups of firms (financially distressed and non-financially distressed), various combinations of predictors across the eight categories were tested. It was expected that financial distress would be negatively related to profit margin, profitability, liquidity, growth from 1998 to 1999 and operating efficiency. Alternatively, financial distress would be positively related to operating or financial leverage. [2]

---

[1] Data from 1998 were also collected to allow measurement of growth rates from 1998 to 1999.
[2] This approach is analogous to the well-known paradigm used by many researchers to predict bankruptcy with prior year data. In our case, instead of bankrupt companies we use those that are severely financially distressed as defined by

The world-wide modeling process began with the variables found to be statistically significant determinants of financial distress for US companies in Platt and Platt (2006). Using an iterative process, a core group of predictors was developed to which additional predictors were added individually. The core set of variables expands as additional factors yield a coefficient with the expected sign, statistical significance, and improved classification accuracy. This approach concentrates on the explanatory power of variables. The selection of the final set of financial and operating ratios was based on their conformity to a priori sign expectations, the statistical significance of estimated parameters and on model classification results.

Model 1 which assumes a single world-wide financial distress prediction framework is compared to a global model that also contains region dummy variables as well as interaction terms of the dummy variables with the financial ratios contained in the model. The model with the additional variables is referred to as Model 2. To test which model specification is best, we use the F-test for nested models (Kmenta, 1986, p. 594). In effect, the two competing models can be characterized as:

Model 1: $\mathbf{y = X_1 \beta_1 + \varepsilon}$

Model 2: $\mathbf{y = X_1 \beta_1 + X_2 \beta_2 + \varepsilon}$

Where X_1 is the set of factors contained in the global model and X_2 is the set of region dummies and the interaction terms which when added to the global model creates Model 2. The null hypothesis states that $\mathbf{\beta_2 = 0}$; alternatively, $\mathbf{\beta_2 \neq 0}$. If the null hypothesis cannot be rejected, then the global model is the best specification regardless of global location. However, if the null hypothesis is rejected, then different specifications for each region is best.

---

a two-year three-screen approach. That is, the technique looks for characteristics in prior year data that distinguishes between future severely financially distressed and non-financially distressed companies.

Model building utilizes logit regression analysis because of its flexibility and statistical power in modeling (McFadden, 1984; Lo, 1986). A non-linear maximum-likelihood estimation procedure obtained estimates of the parameters of the logit model shown in equation (2).

$$P_i = \frac{1}{[1 + \exp^{-(B_0 + B_1 X_{i1} + B_2 X_{i2} + \dots + B_n X_{in})}]} \tag{2}$$

where: P_i = probability of financial distress of the i^{th} firm,

X_{ij} = j^{th} variable of the i^{th} firm, and

B_j = estimated coefficient for the j^{th} variable.

With logit regression, it is possible to test the significance of individual estimated coefficients which is not the case with other estimation methods such as multiple discriminate analysis.

IV. RESULTS

Table 4 presents the means of three key financial ratios by region, financial status and industry. In the interest of brevity, only the three largest industries are presented: chemicals and allied products, industrial machinery and equipment and electrical and electronic equipment. Table 4 shows that companies categorized as financially distressed not only have lower cash flow to sales and lower EBITDA to total assets, but the average ratio is negative across all three regions and across all three industries. By contrast, firms not categorized as financially distressed have higher ratios.

The pattern for total debt to total assets is not as easily described. For all three industries in the US, financially distressed firms had more debt, on average, than reasonably non-financially distressed firms. However, in Europe and in Asia, mixed results were found. In some industries, non-financially distressed firms were found to have more debt than financially distressed firms.

Thus, it is more difficult to make a generalizable statement about debt. It may be that in these regions healthier firms can attract more debt because of their financial strength, whereas weaker firms cannot and thus show less debt. This somewhat counter intuitive result may be characteristic of the chemical industry outside of the US where non-financially distressed firms are able to borrow more to invest in their substantial plant and facilities.

Insert Table 4 about here

The global model (Model 1), shown in Table 5, contains seven variables, one variable each representing profit margin (CF/Sales), profitability (EBITADA/TA), liquidity (CA/CL), operating efficiency (Sales/WC), and operating leverage (DA/EBIT). There are also two financial leverage variables (short term: NP/TA and total: TD/TA). With financially distressed firms arbitrarily coded as 1, negative (positive) coefficients describe an inverse (direct) relationship with financial distress. It is not unreasonable to expect *a priori* that higher cash flow margins (CF/Sales), greater profitability (EBITDA/TA) and greater working capital turnover (Sales/WC) reduce the risk of financial distress; whereas, higher operating leverage (DA /EBIT) and higher financial leverage (short term: NP/TA, total: TD/TA) are likely to increase the risk of financial distress. The remaining variable, liquidity (CA/CL), is more difficult to assess. On the one hand finance textbooks argue that having more liquidity is associated with improved corporate health. On the other hand, a global company that holds too many of its assets (relative to its current liabilities) as current assets is reducing its investment in more profitable fixed assets which may reduce its profitability. Over investment in current assets relative to current liabilities may increase the risk of financial distress.

Insert Table 5 about here

All estimated coefficient receive the expected signs. The current ratio receives a positive coefficient which says that overinvestment in current assets increases the risk of financial distress. Platt and Platt (1991a) found that companies with too many of their assets invested in fixed assets have higher financial distress risk. Our new finding supports the earlier discovery by saying that companies must not over invest in either fixed assets or current assets; there is an appropriate investment level for each.

Further, all but one estimated coefficient is statistically significant beyond the .05 level. The measure of operating leverage, DA/EBIT, is not significant, but was retained in the model because it improved the percentage of firms correctly classified, both overall and for financially distressed firms.

The global financial distress prediction model had an overall correct classification rate of 94.5 percent, as shown in Panel B of Table 5. For the distressed group, the model correctly classified 82.1 percent of companies; for the non-distressed group, 96.4 percent of companies.

Extending the Model to Other Regions

To test whether the factors predictive of financial distress are the same across the three regions in question, we added two region dummy variables to Model 1 as well as interaction terms between the two dummy variables and the seven variables included in the model, yielding 23 total predictors in Model 2. Table 6 presents the Model 2 results, as well as the results for Model 1 for comparison purposes.

Insert Table 6 about here

Estimated coefficient comparisons between the two models show that all main effects continue to have the same relationship to financial distress except for DA/EBIT. In Model 2, DA/EBIT is now marginally significant, but with a negative relationship to financial distress; that is, the greater the operating leverage (use of fixed assets), the lower the likelihood of financial distress. Further, two variables, NP/TA and Sales/WC, are not statistically significant as main effects, but do impact financial distress as interaction terms with one of the region dummy variables.

An F-statistic is used to test whether the additional dummy variables and interaction terms contain significant real explanatory power. Again, the null hypothesis states that region locale has no effect on the model, thus $\mathbf{\beta_2 = 0}$ where $\mathbf{\beta_2}$ represents the additional variables found in Model 2. The particular equation for the F-statistic is shown in equation 3 below.

$$F_{(K_2, n-K_1-K_2)} \approx \frac{(SSE_1 - SSE_2)/K_2}{SSE_2/(n-K_1-K_2)} \tag{3}$$

According to Kmenta (1986, p. 594), Model 1 is best if the F-statistic is less than 1.0. Otherwise, Model 2 is preferred. The calculation indicated an $F_{(23, 3901)} = 4.698$, with $SSE_1 = 154.35$, $SSE_2 = 150.19$, $n = 3931$, $K_1 = 7$, and $K_2 = 23$. Thus, the null hypothesis that the regional location has no effect is rejected. Based on this result, the specific region does affect factors predicting financial distress.

Using the results in Table 6, a marginal change in six of the seven predictors in Model 2 results in differential effects in Europe as compared to the US or Asia. For example, the partial derivative of the probability of financial distress with respect to cash flow to sales is -0.732 for firms in Europe, as compared to -0.096 for US firms and -0.201 for firms in Asia. This finding suggests that a marginal decline in cash flow to sales in Europe has a far more substantial impact in moving that firm toward financial distress than is the case in the US and Asia. Similar differential effects are found for four other variables: return on operating assets before depreciation and amortization, notes payable to total assets, the current ratio, and sales to working capital.

For the operating leverage variable, depreciation and amortization to EBIT, the results have the opposite sign. Europe continues to diverge from Asia and the U.S, but now a marginal increase in operating leverage results in an increase in the probability of financial distress for European firms. By contrast, for companies in the US and Asia, increases in operating leverage are related to reductions in the probability of financial distress. European firms have outsourced much of their manufacturing capacity to emerging markets, such as Eastern Europe, and Asia. Given the outsourcing of manufacturing capacity, increases in operating leverage may indicate a departure from the strategic deployment of assets and thus may be a signal of financial distress.

Comparing the Global Model with Regional Indicators to Three Distinct Regional Models

The estimated coefficients in Model 2 indicate that the relationship between the likelihood of financial distress and all of the variables except TD/TA are significantly different for Europe when compared to the US or to Asia. This result suggests that it may be beneficial to explore whether three *different* models would be superior when predicting financial distress. That is, because manufacturing strategies may differ among the three regions, perhaps based upon indigent industries, their relative size or age, we may find that pooling across the three regions masks key differences that could be exploited during the modeling process. In effect, we can test the following two hypotheses:

H_1: A global model with regional indicators and interaction terms is best [same variables, possibly different coefficients]

H_2: Three separate models by region are best [different variables]

To test the above hypotheses, separate models will be constructed for each of the three regions: US, Europe and Asia. J-tests (Davidson and McKinnon, 1981) will be used to examine whether the incremental information contained in the different, non-nested model specifications is significant. The specific equation considered is:

$$Y = (1\text{-}\alpha)\, \mathbf{X_1 ß_1} + \alpha\, \mathbf{X_2 ß_2} + \varepsilon \qquad (4)$$

where H_1 and H_2 above are indicated by their respective variables and coefficients. Thus, testing H_1 is basically testing whether or not $\alpha = 0$. Because α is not identified, the J-test replaces $\boldsymbol{\beta}_2$ with $\hat{\boldsymbol{\beta}}_2$, where $\hat{\boldsymbol{\beta}}_2$ is the simple least squares estimator defined as $\hat{\boldsymbol{\beta}}_2 = (\mathbf{X}_2'\mathbf{X}_2)^{-1}\mathbf{X}_2'\mathbf{y}$. When H_1 is true, α divided by its standard error is distributed N(0,1). A second test is also performed because of the asymmetry of H_1 and H_2. That is, when we test H_1, we use H_2 to challenge the validity of H_1. However, when we reject H_1, it may be some other model other than H_2 that has caused us to reject H_1. To make a statement about H_2, we conduct a second J-test to test α in the following equation:

$$Y = (1\text{-}\alpha)\, \mathbf{X_2 ß_2} + \alpha\, \mathbf{X_1}\, \hat{\mathbf{ß}}_\mathbf{2} + \varepsilon \qquad (5)$$

which in effect is testing H_2 against H_1. Consistent inferences from the two tests would indicate which of the two models is preferred. Inconsistent results would indicate that neither model is useful to predict financial distress or that the data cannot discriminate between the models.

To construct the individual models for each region, the modeling process began with the ratios in Table 3. An iterative modeling process was used to create the three regional models similar to that used to create the global model. As before, coefficient sign and significance as well as the classification accuracy of the model were important criteria for model assessment. The three individual models are presented in Table 7 and the classification accuracy for each model is presented in Table 8.

Insert Tables 7 and 8 about here

Most notably, all three models contain cash flow margin, EBITDA to total assets and some debt to total asset ratio. Further, the same relationship exists between these variables and the likelihood of financial distress in all three cases; namely, a negative relationship for the profit margin and profitability measures and a positive relationship for the financial leverage ratio.

After that point, there are some similarities between pairs of models, such as both the US and Europe models include a liquidity ratio. As found with Model 1, the higher the liquidity, the more likely the firm is to be financially distressed in both cases. This result may be somewhat counter intuitive, but the multivariate nature of the model requires that all other components are held constant before one assesses the independent effect of liquidity. Thus, holding all other factors constant, firms that do not adequately control their cash or liquid assets do not benefit from returns on those assets which makes it more likely than not that they experience financial distress. It may be a signal that senior management is not deploying liquid assets for the optimal benefit of the firm.

Also, cash flow growth is negatively related to financial distress in both Europe and Asia. It is statistically significant in Europe, but marginally so in Asia. The variable was kept in the Asia model, despite its marginal significance because it substantially improved classification accuracy rates. The Europe model also contains sales growth as a significant factor. As with cash flow growth, sales growth has a negative relationship to financial distress. Thus, greater sales growth is associated with a decreased likelihood of financial distress.

Further, sales turnover is found to be a significant predictor of financial distress for Europe and Asia. In both models, the faster the turnover, the less likely a firm is financially distressed. The Europe and Asia models also include Depreciation and Amortization to EBIT, a measure of operating leverage. While the estimated coefficient for Europe is positive, that for Asia is negative. This discrepancy may indicate a difference in maturity and operating realities of the sample companies. That is, manufacturing firms in Europe most likely are conducting much of their actual operations in off-shore plants in Eastern Europe, India and Asia. Thus, European companies with high operating leverage are more likely to become financially distressed. By contrast, firms in Asia are more likely the source of manufacturing plants; thus, those with high operating leverage are positioned to reap the benefits of increased scale, thereby improving profitability and thus reducing the likelihood of financial distress.

Finally, the Asia model required two country dummy variables, one for Japan (not significant, but improves classification) and one for Singapore (statistically significant). These indicator variables suggest that there is a higher likelihood of financial distress for firms in these countries, before the effects of specific predictors are considered. In the case of Japan, slight increases in EBITDA/TA have substantially larger effects on the likelihood of financial distress than is the case for other Asian countries. More specifically, the large, negative, significant estimated coefficient for the interaction between the Japan dummy variable and EBITDA/TA suggests that slight increases in EBITDA/TA there produce greater reductions in the probability of financial distress as compared to other Asian countries. Given Japan's tenuous economic condition at the turn of the 21st century, it makes sense that any improvement in a company's profitability was a significant signal of financial health.

As discussed above, J-tests are used to test which model specification, if any, is best to predict financial distress among firms across the three regions. The first J-test compared the global model (with interactions and dummy variables) to the separate models for each region. Specifically, the test estimated α in the following equation:

$$Y = (1-\alpha)M_1 + \alpha\hat{M}_2 \tag{6}$$

where M_1 is the global model and M_2 are the separate regional models. The estimated α parameter was 8.475, with p-value of 0.000. Thus, the null hypothesis that α = 0 is rejected, indicating that

M_2, separate models, is best for predicting Y, financial distress. The second J-test was conducted to estimate α in the following equation:

$$Y = (1-\alpha)M_2 + \alpha\hat{M}_1 \tag{7}$$

To test this model specification, individual regional regressions were run. The estimated α parameter for the US model was 1.136 with p-value of 0.396; for Europe, 1.122, with p-value of 0.482; and for Asia, 2.576 with p-value of 0.077. In all three cases, the null hypothesis that $\alpha = 0$ cannot be rejected; hence, M_2 or separate models is best for predicting Y, financial distress. Thus, both J-test results indicate that separate regional models are best for predicting financial distress.

Model Robustness

The three distinct regional models of financial distress have variables in common and variables that are distinct. Clearly the models are heterogeneous but are their predictions and their predictive abilities different? The underlying issue is whether the models are fundamentally different or whether their differences are cosmetic. This question is examined by considering how well each model predicts financial distress at companies in regions other than their own.

For each region, 20 random companies (60 companies in total) are selected from the existing model building data base. In each region ten non-financially distressed companies and ten financially distressed companies are chosen. The data for these companies is then input into the models built for the other two regions. For example, Asian data is input into the European and U.S. models. This process is repeated for all three regions. The analysis considers the robustness of the models and their abilities to evaluate companies from other regions.

None of the models appear to be robust, as seen in Table 9. Focusing primarily on predictions of financial distress, only US data resulted in reasonably good classification accuracy in both the European and Asian models. That is, US data produced classification accuracies for financially distressed firms that were significantly different from chance (Asia Model) or marginally so (Europe Model). Inputting data from either Asia or Europe into the other two models produced classification accuracies that were not significantly different from chance (about 50% classification accuracy).

These results are consistent with the pooling hypothesis test above. That is, the findings suggest that a regional model cannot accurately predict a company's status if that company comes from outside the region. Nonsimilarity between the models implies that financial distress occurs for different reasons around the world. For example, US firms in financial distress tend to struggle with managing their long-term debt load and interest payments. European firms in financial distress have issues with working capital deployment, operating leverage and growth. Finally, Asian companies experiencing financial distress suffer from low turnover, too little operating leverage and high total debt. By contrast, all of the models performed very well with data from other regions with respect to correctly classifying non-financially distressed companies. Companies that are doing well appear to have similar characteristics regardless of location.

Insert Table 9 here

V. CONCLUSION

The outcomes of globalization from dramatically higher rates of imports and exports to the movement of jobs between countries are appearing everywhere more rapidly than most analysts had expected. The typical consumer in America buys cars made in Korea, wine produced in Chile, and fashions from Italy. Likewise consumers in Korea bank at American institutions, people in Chile buy American computers, and consumers in Italy buy wine from California. Given this rapid and overwhelming flow of goods and services between countries, it is not unreasonable to expect that firms across the globe have begun to adopt the same principles for inventory control, working capital management, hiring and firing, and factory utilization. In other words, one might expect firms to behave similarly regardless of which country they might reside.

Corporate similarity might begin with firm formation and continue through to financial distress and bankruptcy. This study examined the tail end of that series of connections. It looks at whether firms on three regions had similar forces affecting them as they moved from strength to financial distress. Using a methodology based upon a multidimensional definition of financial distress the study compiled a list of companies on three regions that were financially distressed. Then using data from two years prior various explanations were tested of how the corporate decline occurred.

The study posed three hypotheses concerning the form of the models explaining financial distress on the three regions. The null hypothesis assumed that a single global model would explain financial distress on each region. The two alternate hypotheses relaxed this assumption in various degrees. The null hypothesis was rejected in favor of a fully relaxed model which created individual financial distress models for each region.

That globalization has not resulted in similar factors influencing corporate financial strength has macroeconomic implications. Differences between companies in the three regions and their operating ratios are shown in the paper to be dramatic. Factory age and efficiency, unionization, benefit payments as a supplement to wage levels, relationships with lenders and vendors are just some of the many differences one notes across regions. For example, as more production is moved to factories in Asia there is reason to be concerned about the health of the global economy due to the factors related to financial distress in Asian companies. Our results suggest that Asian companies are more likely to become financially distressed when they do not have sufficient operating leverage to support sales volume or do not generate sufficient cash flow or operating earnings before depreciation charges.

VI. REFERENCES

Altman, E.I. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *Journal of Finance,* Vol. 23, 589-609.

Altman, E.I. and H. Izan (1984), "Identifying Corporate Distress in Australia: An Industry Relative Analysis," Working Paper, New York University.

_________, G. Marco, and F. Varetto (1994), "Corporate Distress Diagnosis: Comparisons using Linear Discriminant Analysis and Neural Networks (the Italian Experience)." *Journal of Banking and Finance* Vol. 18, 505-529.

Asquith P, R. Gertner and D. Scharfstein (1994), "Anatomy of Financial Distress: An Examination of Junk-bond Issuers." *Quarterly Journal of Economics,* Vol. 109, No. 3, 1189-1222.

Beaver, W. (1966), "Financial Ratios as Predictors of Failures." *Journal of Accounting Research,* Vol. 4 (Supplement), 71-102.

Brown, D. T., C. M. James, and R. M Mooradian (1992), "The Information Content of Distressed Restructurings Involving Public and Private Debt Claims." *Journal of Financial Economics,* Vol. 33, 92-118.

Davidson, R. and J. McKinnon (1981), "Several Tests for Model Specification in the Presence of Alternative Hypotheses." *Econometrica,* Vol. 49, 781-793.

Dixon , W. J. and F. J. Massey, Jr. (1969), *Introduction to Statistical Analysis*, 3rd edition. New York: McGraw Hill.

Frydman, H., E. I. Altman, and D. Kao (1985), "Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress." *Journal of Finance,* Vol. 60, No. 1, 269-291.

Gilson, S.C. (1989), "Management Turnover and Financial Distress." *Journal of Financial Economics,* Vol. 25, 241-262.

_________, K. John, and L. H. P. Lang (1990), "Troubled Debt Restructurings: An Empirical Study of Private Reorganization of Firms in Default." *Journal of Financial Economics,* Vol. 27, 315-353.

Hausman, J., H. Ichimura, W. Newey and J. Powell (1991), "Measurement Errors in Polynomial Regression Models." *Journal of Econometrics*, Vol. 50, 271-295.

Hofer, C. W. (1980),"Turnaround Strategies." *Journal of Business Strategy*, Vol. Summer, 19-31.

Hill, N. T., S. E. Perry, and S. Andes (1996), "Evaluating Firms in Financial Distress: An Event History Analysis." *Journal of Applied Business Research,* Vol. 12, No. 3, 60-71.

John, K, L. H. D. Lang and J. Netter (1992), "The Voluntary Restructuring of Large Firms in Response to Performance Decline." *Journal of Finance,* Vol. 47, 891-917.

Kmenta, J. (1986), *Elements of Econometrics*, (New York: Macmillan Publishing Company).

Lachenbruch, P. (1967), "An Almost Unbiased Method of Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis," *Biometrics,* Vol. 23, 639-645.

Lau, A. H. (1987), "A Five-State Financial Distress Prediction Model." *Journal of Accounting Research,* Vol. 25, No. 1, 127-138.

Lev, B. (1969), "Industry Averages as Targets for Financial Ratios," *Journal of Accounting Research*, Vol. 7, 290-299.

Lin, P., L. Ko, and E. Blocher (1999), "Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System." presented at the 1999 Annual Meetings of the American Accounting Association, San Diego.

Lo, A. (1986), "Logit versus Discriminant Analysis: A Specification Test and Application to Corporate Bankruptcy." *Journal of Econometrics,* Vol. 31**,** 151-178.

Mensah, Y. M. (1984), "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study." *Journal of Accounting Research,* Vol. 22, 380-395.

Ohlson, J.A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research*, Vol. 19, 109-131.

Platt, H. and M. B. Platt (1991a), "A Note on the Use of Industry-Relative Ratios in Bankruptcy Prediction," *Journal of Banking and Finance*, Vol. 15, 1183-1194.

____________________ (2002), "Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias," *Journal of Economics and Finance,* Vol. 26, No. 2, 184-199.

____________________ (2006), "Understanding Differences Between Financial Distress and Bankruptcy," *Review of Applied Economics,* Vol. 2, No. 2, 211-227.

PricewaterhouseCoopers (2001), International Accounting Standards: Similarities and Differences.

Schipper, K. (1977), "Financial Distress in Private Colleges." *Journal of Accounting Research,* Vol. 15, (Supplement), 1-40.

Shumway, T. (2001), "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business*, Vol. 74, No. 1, 101-124.

Thedodossious, P, E. Kayha, R. Saidi, and G. Philippatos (1996), "Financial Distress and Corporate Acquisitions: Further Empirical Evidence." *Journal of Business Finance and Accounting,* Vol. 23, No. 5&6, 699-719.

Whitaker, R. B. (1999), "The Early Stages of Financial Distress." *Journal of Economics and Finance*, Vol. 23, No. 2, 123-133.

Yang, A. R., M. B. Platt and H. D. Platt (1999), "Probabilistic Neural Networks in Bankruptcy Prediction." *Journal of Business Research,* Vol. 44, No. 2, 67-74.

Zmijewski, M.E. (1984), "Methodological Issues Related to the Estimation of Financial Distress Prediction Models." *Journal of Accounting Research,* Vol. 22, (Supplement), 59-82.

Table 1
Distressed and Not Distressed Companies in 14 Industries

Industry SIC Code	**Industry Name**	**US**		**Europe**		**Asia**		**Total**	
		H	***FD***	***H***	***FD***	***H***	***FD***	***H***	***FD***
2200	Textile Mill Products	19	4	37	4	71	11	127	19
2300	Apparel & Other Textile	54	7	38	1	45	3	137	11
2600	Paper & Allied Products	63	5	50	1	65	2	178	8
2800	Chemicals	87	14	145	20	320	10	552	44
2900	Petroleum & Coal	27	4	20	0	32	4	79	8
3000	Rubber	69	9	48	3	85	6	202	18
3100	Leather	19	2	7	1	7	2	33	5
3200	Stone, Clay, Glass & Concrete	35	2	94	2	100	12	229	16
3300	Primary Metals	88	12	82	1	135	7	305	20
3400	Fabricated Metals	79	6	59	4	90	8	228	18
3500	Industrial Machinery & Equipment	164	83	167	22	286	21	617	126
3600	Electrical & Electronic Equipment	217	46	148	33	310	18	675	97
3700	Transportation Equipment	80	27	79	4	156	6	315	37
3800	Instruments & Related Products	234	137	94	22	73	4	401	163
	Totals	*1235*	*358*	*1068*	*118*	*1775*	*114*	*4078*	*590*

Table 2
Variables Used to Define Financial Status – Values for Select Industries by Continent

Industry SIC	Financial Status	EBITDA Interest Coverage (00)[3]		EBITDA Interest Coverage (01)		EBIT (00)		EBIT (01)		Net Income before Special Items (00)[4]		Net Income before Special Items (01)	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
US													
2800	NFD	986.21	144.75	1130.42	184.20	784.99	112.58	929.64	154.54	754.35	95.20	921.19	102.57
2800	FD	-23.28	-10.56	-26.89	-14.60	-23.88	-10.96	-27.62	-14.51	-25.34	-10.99	-28.98	-15.16
3500	NFD	391.24	58.07	494.30	85.49	285.93	40.26	393.14	67.13	264.32	30.36	377.36	52.29
3500	FD	-8.43	-3.36	-5.36	-2.89	-12.31	-3.49	-8.03	-3.07	-12.70	-3.77	-7.88	-3.42
3600	NFD	406.21	33.01	489.15	44.80	283.21	23.06	353.61	31.19	318.21	18.79	415.46	29.09
3600	FD	-18.88	-5.38	-16.16	-6.41	-23.21	-6.36	-19.56	-6.87	-24.70	-7.11	-20.42	-7.71
Europe													
2800	NFD	862.81	90.50	1019.17	85.90	763.04	55.20	1447.45	436.80	581.90	48.54	756.61	52.02
2800	FD	-53.68	-15.95	-50.59	-11.92	-54.16	-14.11	-55.14	-15.10	-65.94	-14.71	-56.35	-11.98
3500	NFD	309.87	32.59	373.57	43.85	283.94	36.28	572.03	54.64	190.24	18.96	266.02	26.16
3500	FD	-27.17	-13.85	-26.57	-10.09	-27.77	-11.75	-37.88	-35.01	-28.53	-14.86	-27.76	-12.66
3600	NFD	336.85	32.05	351.76	34.52	246.05	24.02	340.59	27.85	222.05	17.99	248.35	23.68
3600	FD	-31.07	-14.05	-18.96	-8.51	-24.41	-9.89	-16.11	-6.32	-40.71	-19.61	-26.97	-10.12
Asia													
2800	NFD	203.68	24.94	346.33	27.66	155.74	16.44	289.62	19.67	179.97	13.74	343.15	14.88
2800	FD	-64.00	-15.32	-80.73	-11.67	-65.50	-9.69	-76.90	-13.77	-82.27	-13.85	-159.13	-12.58
3500	NFD	408.49	9.12	507.74	12.22	322.80	7.17	392.07	9.08	386.23	6.24	424.16	7.87
3500	FD	-37.77	-2.80	-53.87	-3.68	-36.18	-3.51	-52.06	-3.97	-63.96	-3.23	-67.59	-4.31
3600	NFD	909.13	21.23	1256.42	23.18	445.39	14.24	722.10	17.12	443.61	12.58	736.53	13.46
3600	FD	-67.60	-5.58	-79.50	-5.65	-169.74	-7.45	-168.85	-6.23	-241.55	-12.55	-228.68	-6.64

[3] EBITDA – Interest expense
[4] Net income + Special items (US); Net income before extraordinary items – Extraordinary items + Special items (Non US)

Table 3
Data and Financial Ratios Employed

Individual Financial Items		**Financial Ratios**		
Status	Inventories (Inv)	***Profit Margin***	***Liquidity***	***Operating Efficiency***
Net Sales (S)	Inv (-1)	EBITDA/S	CA/CL	COGS/Inv
S (-1)[5]	Current Assets (CA)	NI/S	(CA-Inv)/CL	S/AR
COGS	CA (-1)	CF/S	WC/TA	S/TA
COGS (-1)	Net Fixed Assets (NFA)	***Profitability***	CA/TA	AR/TA
Deprec+Amort (DA)	NFA (-1)	EBITDA/TA	NFA/TA	S/WC
DA (-1)	Total Assets (TA)	NI/TA	***Cash Position***	S/Inv
SGA	TA (-1)	EBIT/TA	Cash/CL	AR/Inv
SGA (-1)	Accounts Payable (AP)	CF/TA	Cash/DA	(AR+Inv)/TA
EBIT	AP (-1)	NI/EQ	Cash/TA	COGS/S
EBIT (-1)	Notes Payable (NP)	***Financial Leverage***	***Growth***	SGA/S
Interest Expense (Int)	NP (-1)	TL/TA	S-Growth %	(COGS+SGA)/S
Int (-1)	Current Liabilities (CL)	CL/TA	NI/TA-Growth %	DA/S
Net Income (NI)	CL (-1)	CL/TL	CF-Growth %	DA/EBIT
NI (-1)	Long-term Debt (LTD)	NP/TA	***Miscellaneous***	S/CA
Cash	LTD (-1)	NP/TL	EBIT/Int	
Cash (-1)	Total Liabilities (TL)	LTD/TA	Int/S	
Accounts Receivable (AR)	TL (-1)	Current LTD/TA	LTD/S	
AR (-1)	Share Equity (EQ)	EQ/TA	CF/Int	
	EQ (-1)	LTD/EQ	CF/TL	
		TD/TA		
Calculated Items				
EBITDA = EBIT + DA				
EBITDA(-1) = EBIT (-1) + DA (-1)				
CF = NI + DA				
WC = CA - CL				

[5] Variable values specified as VARIABLE (-1) were collected in 1998. Otherwise, the variable value was collected in 1999. Thus, growth variables indicate growth rates from 1998 to 1999.

Table 4
Descriptive Statistics across Regions, SIC Code[6] and Status

	US		Europe		Asia	
	NFD[7]	FD	NFD	FD	NFD	FD
CF/Sales						
2800	0.087	-0.954	0.118	-6.510	0.097	-0.674
3500	0.063	-1.856	0.083	-4.444	0.068	-0.297
3600	0.192	-0.433	0.104	-2.001	0.103	-0.266
EBITDA/TA						
2800	0.120	-0.448	0.138	-0.372	0.109	-0.075
3500	0.116	-0.828	0.126	-0.100	0.086	-0.026
3600	0.132	-0.696	0.160	-0.350	0.104	-0.110
TD/TA						
2800	0.324	0.411	0.205	0.165	0.245	0.152
3500	0.240	0.356	0.208	0.196	0.227	0.383
3600	0.235	0.445	0.180	0.172	0.221	0.325

[6] SIC 2800 is the chemicals and allied products industry; SIC 3500 is the industrial machinery and equipment industry; SIC 3600 is the electrical and electronic equipment industry.
[7] NFD indicates companies that are non-financially distressed; FD indicates companies that are financially distressed.

Table 5
Estimated Coefficients for the Global Model
Dependent Variable is Categorical (1 if financially distressed and 0 otherwise)

Variables	**Estimated Coefficient**	***p*-value (two-tail)**
CF/Sales	-0.141	.001**
EBITDA/TA	-2.129	.000**
CA/CL	0.390	.000**
Sales/WC	-0.022	.028*
DA/EBIT	0.004	.447
NP/TA	0.043	.042*
TD/TA	0.471	.000**
Constant	-2.440	.000**

Nagelkerke R^2 = .702
* Significant beyond the .05 level of significance
** Significant beyond the .01 level of significance

Where:
CF/Sales = Net Cash Flow/Sales
EBITDA/TA = Earnings before interest, taxes, depreciation and amoritization/Total Assets
CA/CL = Current Assets/Current Liabilities
Sales/WC = Sales/Working Capital
DA/EBIT = Depreciation and amortization/EBIT
NP/TA = Notes Payable/Total Assets
TD/TA = Total Debt/Total Assets

Classification Results

Group Classified	**Percent Classified Correctly**
Non-financially distressed companies	96.4%
Financially Distressed companies	82.1%
All companies	94.5%

Table 6
Comparison of the Global Model (Model 1) to the
Global Model with Regional Indicators (Model 2)

	Global Model Model 1		**Global Model with Regional Indicators Model 2**	
Variable	**Estimated Coefficient**	**p-value**	**Estimated Coefficient**	**p-value**
CF/Sales	-0.141	.001***	-0.096	.012**
EBITDA/TA	-2.129	.000***	-1.992	.000***
CA/CL	0.390	.000***	0.273	.013**
Sales/WC	-0.022	.028**	-0.003	.860
DA/EBIT	0.004	.447	-0.018	.061*
NP/TA	0.043	.042**	0.031	.173
TD/TA	0.471	.000***	0.402	.002***
Dummy Europe (E)			-0.481	.414
Dummy Asia (A)			-0.571	.255
CF/Sales E			-0.636	.007***
EBITDA/TA E			0.670	.081*
CA/CL E			0.633	.027**
Sales/WC E			-0.211	.027**
DA/EBIT E			0.059	.001***
NP/TA E			0.321	.050**
TD/TA E			-0.387	.244
CF/Sales A			-0.105	.363
EBITDA/TA A			-0.396	.265
CA/CL A			0.170	.462
Sales/WC A			-0.035	.196
DA/EBIT A			0.010	.543
NP/TA A			-0.003	.983
TD/TA A			0.257	.324
Constant	-2.440	.000***	-2.245	.000***
Nagelkerke R^2		.702		.716

* Significant beyond the .10 level of significance
** Significant beyond the .05 level of significance
*** Significant beyond the .01 level of significance

Table 7
Estimated Coefficients for Asia, Europe, and U.S. Models^

Variables	**US**	**Europe**	**Asia**
CF/Sales	-0.128***	-1.090**	-0.714***
EBITDA/TA	-2.484***	-3.974***	-2.256***
Debt/TA	0.123*** (Current LTD/TA)	0.632** (NP/TA)	0.634* (TD/TA)
Interest Coverage Before Tax	-0.084		
Liquidity Ratio	0.269** ([CA-Inv]/CL)	1.820*** (CA/CL)	
Sales Turnover		-0.356* (S/WC)	-1.918** (S/TA)
DA/EBIT		0.068***	-0.338***
% Change in Sales		-0.964***	
% Change in Cash Flow		-0.082***	-0.010#
Japan Dummy			1.002
Singapore Dummy			2.384**
Japan x EBITDATA			-9.138***
Constant	-4.298***	-4.436***	-2.566***
Nagelkerke R^2	0.726	0.689	0.565

^*Coefficients are scaled. All estimated coefficients are the property of BBK, Ltd.*
Dependent Variable is Categorical (1 if financially distressed and 0 otherwise)
* Significant beyond the .10 level of significance, two-tailed.
** Significant beyond the .05 level of significance, two-tailed.
*** Significant beyond the .01 level of significance, two-tailed.
\# Significant beyond the .10 level of significance, one-tailed.

Table 8
Classification Accuracy in Asia, Europe, and U.S. Models

Group Classified	US	Europe	Asia
Non-financially distressed Companies	94.8% n = 1,127	97.0% n = 908	95.4% n = 1,056
Financially Distressed Companies	87.0% n = 276	81.2% n = 101	81.3% n = 80
All Companies	93.2% n = 1,403	95.4% n = 1,009	94.4% n = 1,136

Table 9
Comparing Model Predictions Using Data from Other Regions

Model	Source of Data	Accuracy of Financial Distress Classification	Accuracy of Non-financially distressed Classification
Asian	Europe	60%	100%
Asian	U.S.	100%	80%
European	Asia	50%	100%
European	U.S.	80%	80%
U.S.	Asia	10%	100%
U.S.	Europe	60%	100%